

# AOL ANALYSIS WEATHER EVENTS

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# Presentation Outline



1. Analysis Goals
2. External Dataset
3. Overall Database Schema (Pre Slicing)
4. The 5 Questions

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# Analysis Goals

1. Understand the characteristics of weather events of March to May 2006
- &
2. Analyze how weather events impacted people's browsing behavior

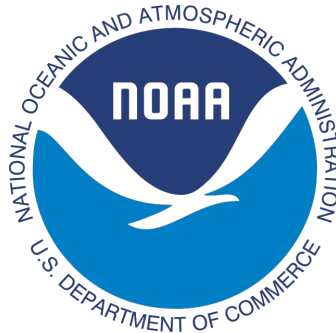
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# External Dataset

# Data-Source

## NOAA Storm Events Database

- ❑ By the National Oceanic and Atmospheric Association (NOAA), specifically the National Weather Service (NWS)
- ❑ **Official Data:** NOAA as part of the US Department of Commerce offers scientifically accurate weather data



# Storm Events Database



**Weather event:** A specific weather occurrence, like storms, floods, or heatwaves, confined to a particular time and place

## Dimensions:

- ❑ Time (Begin and End)
- ❑ Event Type (e.g. Tornado, Drought, Hailstorm)
- ❑ Location
- ❑ Deaths and Injuries
- ❑ Monetary damage (Crops and Property)

```
CREATE TABLE AOL_SCHEMA.WEATHER_EVENTS (  
    BEGIN_DATE_TIME TIMESTAMP,  
    END_DATE_TIME TIMESTAMP,  
    EVENT_TYPE VARCHAR(100),  
    REGION VARCHAR(100),  
    BEGIN_DAY INTEGER,  
    END_DAY INTEGER,  
    BEGIN_MONTH INTEGER,  
    END_MONTH INTEGER,  
    INJURIES_DIRECT INTEGER,  
    INJURIES_INDIRECT INTEGER,  
    DEATHS_DIRECT INTEGER,  
    DEATHS_INDIRECT INTEGER,  
    DAMAGE_PROPERTY INTEGER,  
    DAMAGE_CROPS FLOAT,  
    EPISODE_ID INT,  
    EVENT_ID INT NOT NULL,  
    PRIMARY KEY (EVENT_ID)  
)
```

# Preprocessing

```
def convert_abbreviated_string(value):
    # Check for 'k' (thousand), 'm' (million), 'b' (billion)
    if isinstance(value, str):
        print(value)
        if 'k' in value.lower():
            return float(value.replace('k', '').replace('K', '')) * 1000
        elif 'm' in value.lower():
            return float(value.replace('m', '').replace('M', '')) * 1000000
        elif 'b' in value.lower():
            return float(value.replace('b', '').replace('B', '')) * 1000000000
        else:
            # If no abbreviation, just return the float version of the number
            try:
                return float(value)
            except ValueError:
                return None # or handle invalid strings as needed
    return value
```

- ❑ Alter the format of the “counts of damages”

- ❑ Remove duplicate rows

```
# Replace NaN values with None
df = df.where(pd.notnull(df), None)
print(df.shape)

# Remove duplicates based on all columns except 'EVENT_ID'
columns_except_event_id = df.columns[df.columns != 'EVENT_ID']

# Drop duplicates based on all columns except 'EVENT_ID'
distinct_df = df.drop_duplicates(subset=columns_except_event_id)
```

---

# Database Schema



# Database-Schema

## NOAA DATA

WEATHER_EVENTS		
INT	Event_ID	PK
INT	Episode_ID	
DATETIME	Begin_Date_Time	
DATETIME	End_Date_Time	
INT	Begin_Day	
INT	End_Day	
INT	Begin_Month	
INT	End_Month	
STRING	Event_Type	
STRING	Region	
INT	Injuries_Direct	
INT	Injuries_Indirect	
INT	Deaths_Direct	
INT	Deaths_Indirect	
DOUBLE	Damage_Property	
DOUBLE	Damage_Crops	

## AOL DATA

TIMEDIM		
INT	TimeID	PK
INT	Year	
INT	Month	
INT	Day	
INT	Hour	
INT	Minute	
INT	Seconds	

FACTS		
INT	FactID	PK
INT	AnonID	FK
INT	QueryID	FK
INT	TimeID	FK
INT	URLID	FK
INT	IRank	
INT	Click	

ANONID		
INT	AnonID	PK
INT	ID	

QUERYDIM		
INT	QueryID	PK
String	Query	

URLDIM		
INT	URLID	PK
STRING	URL	
STRING	Title	
STRING	Description	
STRING	Protocol	
STRING	Path	

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# Our Questions

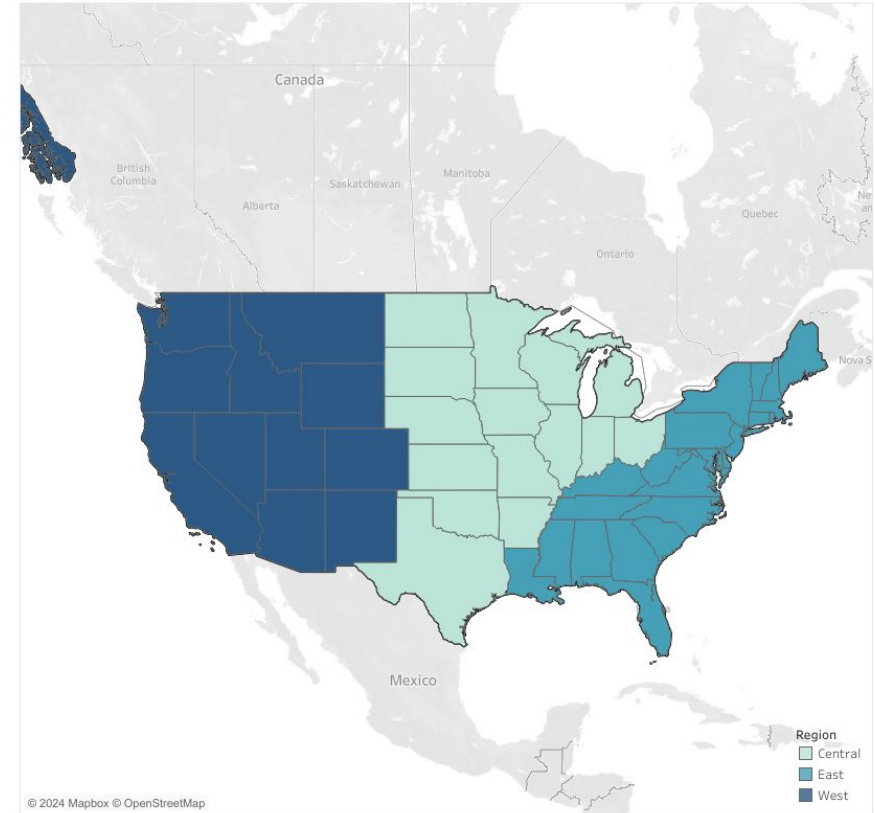
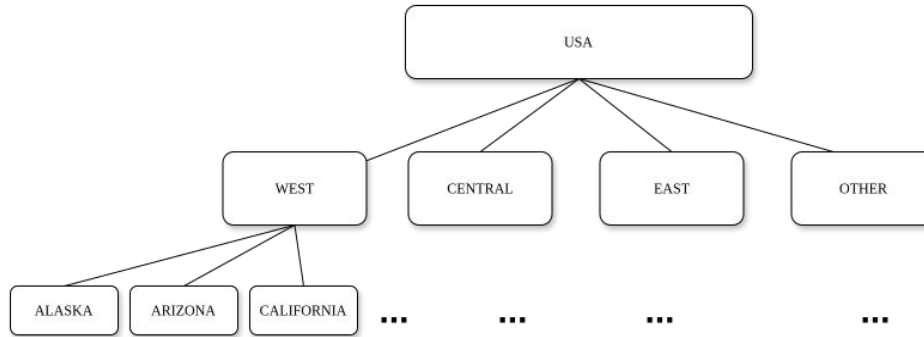
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**Question 1:**

**When and where have weather events  
been most destructive?**

# Spatial Hierarchy

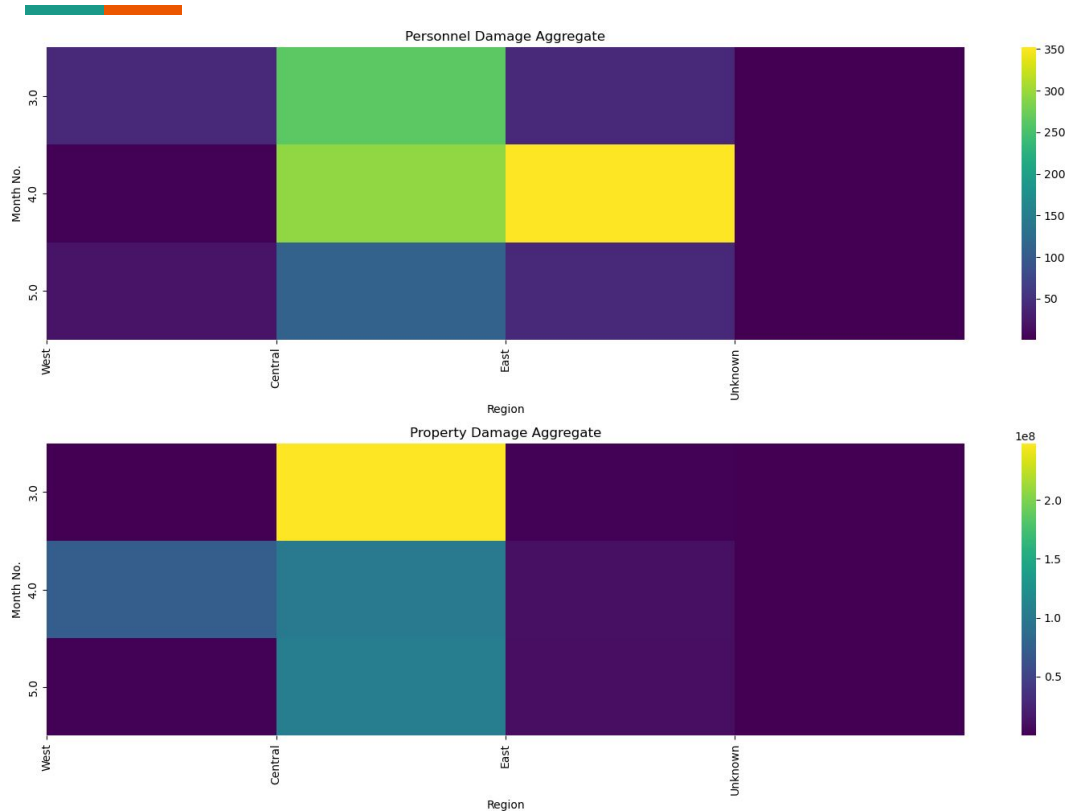
- ❑ We group the US states into **4 Regions**: West, Central, East and Other (e.g. Guam, Puerto Rico or American Samoa)



# Query

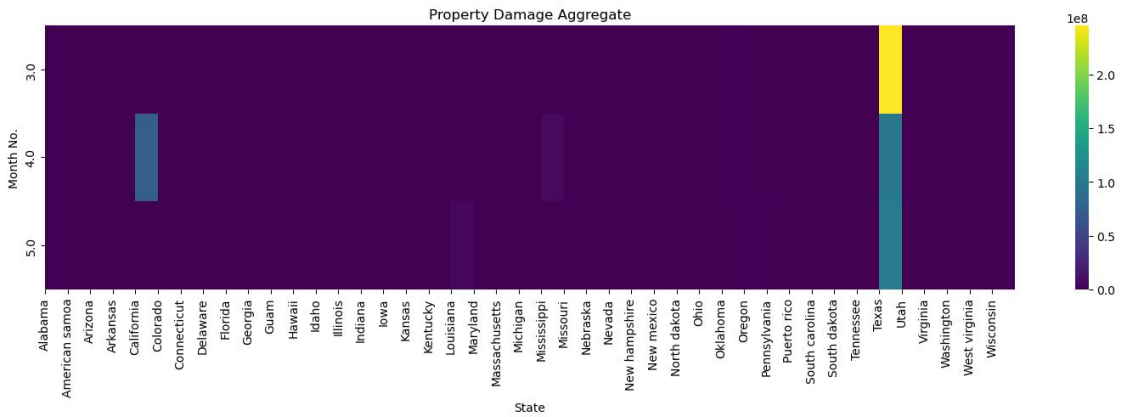
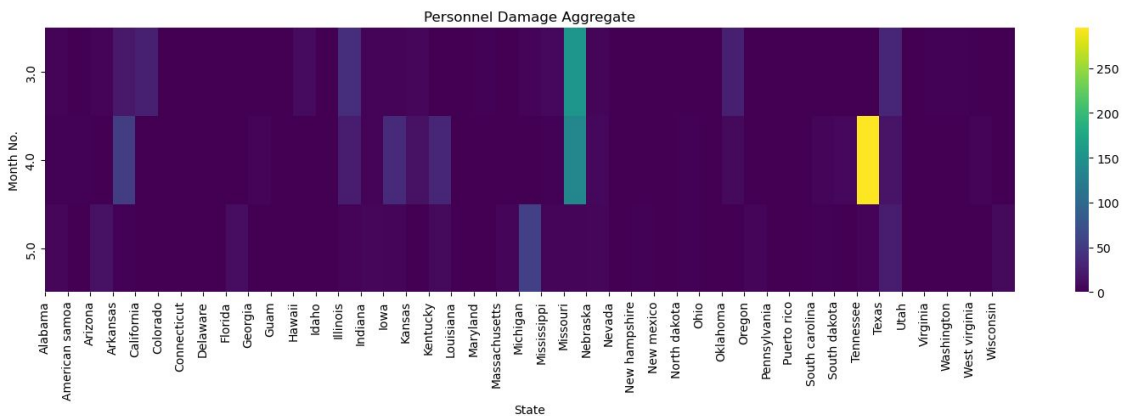
```
WITH NewWeatherData AS (
  SELECT
    MONTH(BEGIN_DATE_TIME) AS BEGIN_MON,
    REGION,
    CASE
      -- West Region
      WHEN STATE_FIPS IN ('02', '04', '06', '08', '15', '16', '30', '32', '35', '41', '49', '53', '56')
      THEN 'West'
      -- Central Region
      WHEN STATE_FIPS IN ('05', '17', '18', '19', '20', '26', '27', '29', '31', '38', '39', '46', '48', '55')
      THEN 'Central'
      -- East Region
      WHEN STATE_FIPS IN ('01', '09', '10', '11', '12', '13', '21', '22', '23', '24', '25', '28', '33', '34', '36', '37', '40', '42', '44', '45', '47', '50',
      '51', '54')
      THEN 'East'
      ELSE 'Unknown'
    END AS TRISECTION,
    COALESCE (INJURIES_DIRECT, 0) + COALESCE (INJURIES_INDIRECT, 0) + COALESCE(DEATHS_DIRECT, 0) + COALESCE(DEATHS_INDIRECT, 0) AS HUMAN_DAMAGE,
    COALESCE(DAMAGE_PROPERTY, 0) + COALESCE (DAMAGE_CROPS, 0) AS NON_HUMAN_DAMAGE
  FROM
    AOL_SCHEMA.WEATHER_EVENTS
  WHERE
    MONTH(BEGIN_DATE_TIME) >= 3.0
)
SELECT
  BEGIN_MON,
  REGION,
  TRISECTION,
  SUM(HUMAN_DAMAGE) AS TOTAL_HUMAN_DAMAGE,
  SUM(NON_HUMAN_DAMAGE) AS TOTAL_NON_HUMAN_DAMAGE
FROM
  NewWeatherData
GROUP BY
  CUBE (BEGIN_MON, REGION, TRISECTION)
HAVING
  SUM(HUMAN_DAMAGE) > 0
  AND SUM(NON_HUMAN_DAMAGE) > 0
ORDER BY
  BEGIN_MON,
  TRISECTION,
  REGION;
```

# Region Aggregates Heatmaps



- Many injuries/deaths in the East in April.
- Most property damage was in the Central region in March.
- The Central region incurred the most property damage throughout the period.

# State-wise Aggregate Heatmaps

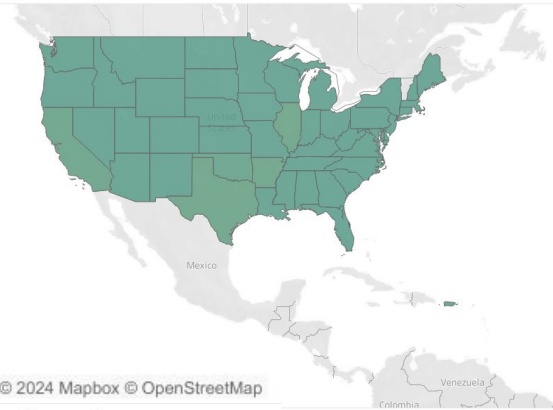


- Tennessee in April had the most injuries/deaths.
- Missouri had many injuries/deaths in March and April
- Texas had the most property damage across all months with March being the worst.
- California also had some property damage in April.

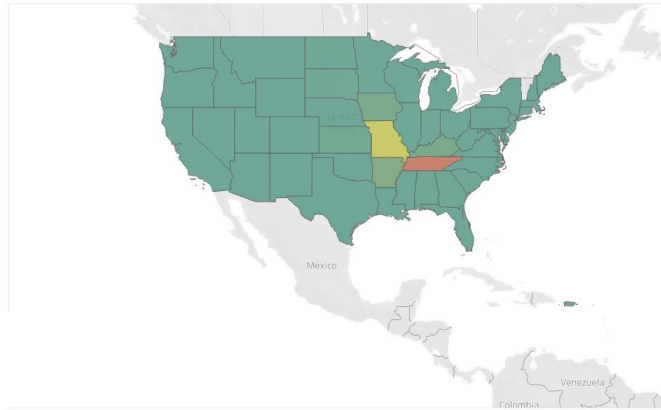
# Deaths and Injuries by Natural Disasters over Time

- ☐ Most dangerous month: **April** with 651 injuries and deaths

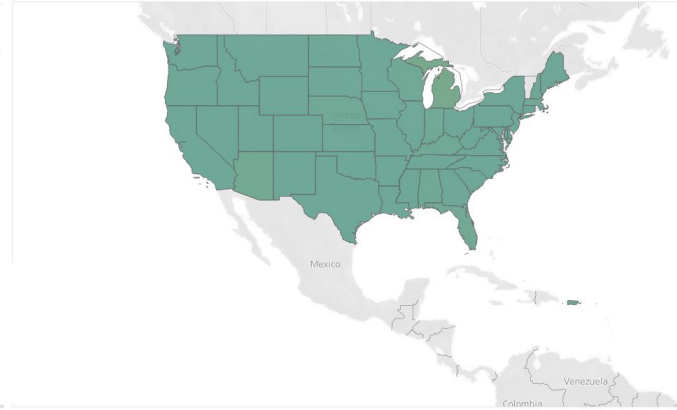
March



April



May



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Human Damage

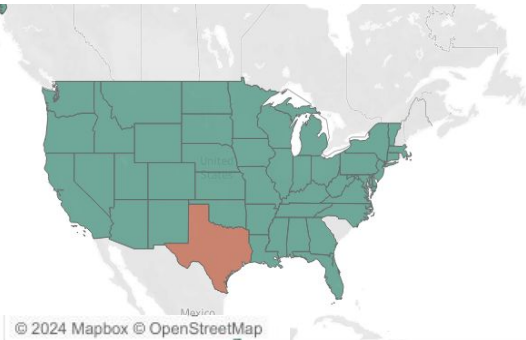
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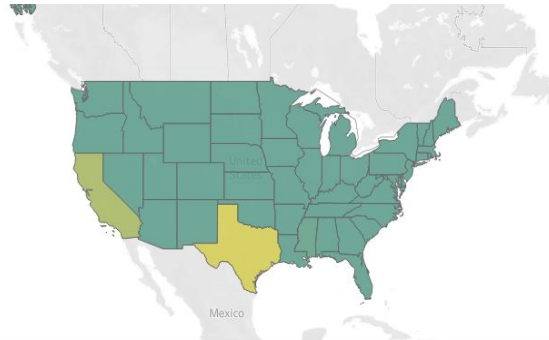
# Damage from natural disasters in USD over Time

☐ Month with most damage to property: **March** with \$251 Mio.

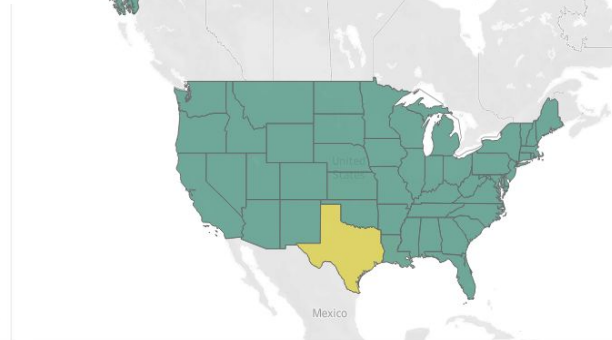
March



April



May



Total Destruction

0 245,780,000

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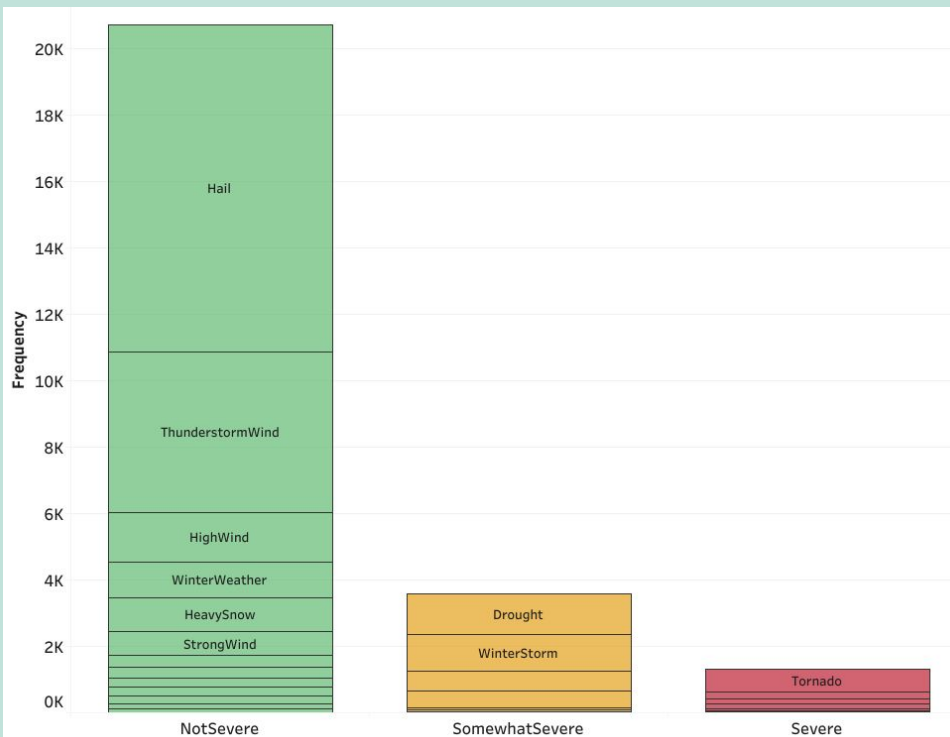
## Question 2:

**What are the types of events that we observe and how do they change over time?**

# Query (Questions 2 & 3)

```
WITH SEVERITY_TABLE AS(
  SELECT
    EVENT_ID,
    EVENT_TYPE,
    BEGIN_DATE_TIME,
    CASE
      WHEN WEATHER_EVENTS.EVENT_TYPE IN ('Blizzard', 'Tornado', 'Wildfire', 'Avalanche', 'Funnel Cloud', 'Waterspout',
      'Debris Flow') THEN 'Severe'
      WHEN WEATHER_EVENTS.EVENT_TYPE IN ('Coastal Flood', 'Flash Flood', 'Flood', 'Drought', 'Dust Devil', 'Dust Storm',
      'Storm Surge/Tide', 'Ice Storm', 'Winter Storm') THEN 'Somewhat Severe'
      WHEN WEATHER_EVENTS.EVENT_TYPE IN ('Cold/Wind Chill', 'Frost/Freeze', 'Heat', 'Heavy Rain', 'Heavy Snow', 'High
      Wind', 'Strong Wind', 'Thunderstorm Wind', 'Winter Weather', 'Lightning', 'Marine High Wind', 'Marine Thunderstorm Wind',
      'Sleet', 'WINTER WEATHER', 'High Surf', 'Marine Hail', 'Rip Current', 'Lake-Effect Snow', 'Dense Fog') THEN 'Not Severe'
      ELSE 'Unclassified'
    END AS SEVERITY
  FROM AOL_SCHEMA.WEATHER_EVENTS
),
AGG_EVENTS AS(
  SELECT
    SEVERITY,
    EVENT_TYPE,
    COALESCE(COUNT(EVENT_ID),0) AS FREQ
  FROM SEVERITY_TABLE
  GROUP BY ROLLUP(SEVERITY, EVENT_TYPE)
)
SELECT
  SEVERITY,
  EVENT_TYPE,
  FREQ,
  RANK() OVER(PARTITION BY SEVERITY ORDER BY FREQ DESC) as RANKING
FROM AGG_EVENTS
;
```

# Weather Events by Severity



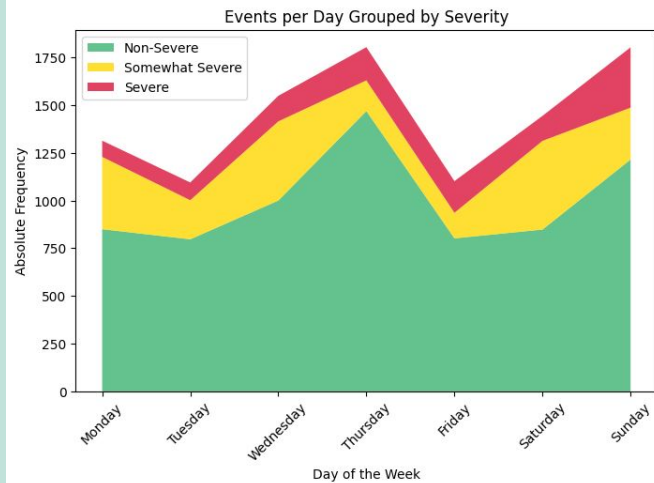
- ❑ **Cold and Wind** related weather events make up the majority of frequent weather events
- ❑ **Tornados** make up the majority of severe weather events
- ❑ Overall: about 26k recorded weather events in 92 days

# Query

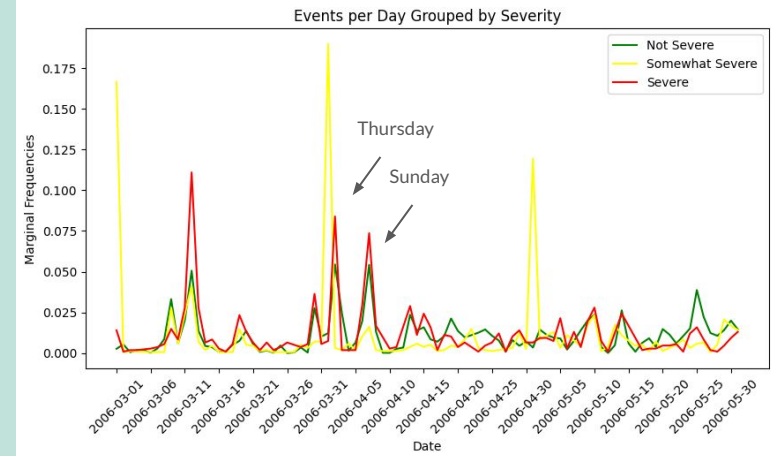
## (Questions 2 & 3)

```
WITH DATE_RANGE AS (  
    SELECT DATE '2006-03-01' AS EVENT_DATE  
    UNION ALL SELECT DATE '2006-03-02'  
    .  
    .  
    UNION ALL SELECT DATE '2006-05-31'  
)  
,  
SEVERITY_TABLE AS(  
SELECT  
    EVENT_TYPE,  
    EVENT_ID,  
    CAST(WEATHER_EVENTS.BEGIN_DATE_TIME AS DATE) AS BEGIN_DATE,  
    WEEK(WEATHER_EVENTS.BEGIN_DATE_TIME) AS BEGIN_WEEK,  
    (MOD(CAST(CAST(WEATHER_EVENTS.BEGIN_DATE_TIME AS DATE) - CAST('2006-01-01' AS DATE) AS INTEGER) + 6, 7) + 1) AS WEEKDAY,  
    CASE  
        WHEN WEATHER_EVENTS.EVENT_TYPE IN ('Blizzard', 'Tornado', 'Wildfire', 'Avalanche', 'Funnel Cloud', 'Waterspout') THEN 'Severe'  
  
        WHEN WEATHER_EVENTS.EVENT_TYPE IN ('Coastal Flood', 'Flash Flood', 'Flood', 'Drought', 'Dust, Devil',  
                                             'Dust Storm', 'Storm Surge/Tide') THEN 'Somewhat Severe'  
  
        WHEN WEATHER_EVENTS.EVENT_TYPE IN ('Cold/Wind Chill', 'Frost/Freeze', 'Heat', 'Heavy Rain', 'Heavy Snow', 'Hail', 'High Wind', 'Strong Wind', 'Thunderstorm Wind',  
                                             'Winter Weather', 'Lightning', 'Marine High Wind', 'Marine Thunderstorm Wind', 'Sleet', 'WINTER WEATHER',  
                                             'Winter Storm') THEN 'Not Severe'  
  
        ELSE 'Unclassified'  
    END AS SEVERITY  
FROM AOL_SCHEMA.WEATHER_EVENTS  
)  
  
SELECT  
    DATE_RANGE.EVENT_DATE,  
    SEVERITY_TABLE.BEGIN_WEEK,  
    SEVERITY_TABLE.WEEKDAY,  
    SEVERITY_TABLE.SEVERITY,  
    SEVERITY_TABLE.EVENT_TYPE,  
    COALESCE(COUNT(SEVERITY_TABLE.EVENT_ID), 0) AS FREQ  
FROM DATE_RANGE  
  
LEFT JOIN SEVERITY_TABLE  
ON DATE_RANGE.EVENT_DATE = SEVERITY_TABLE.BEGIN_DATE  
  
GROUP BY ROLLUP((DATE_RANGE.EVENT_DATE, SEVERITY_TABLE.BEGIN_WEEK, SEVERITY_TABLE.WEEKDAY, SEVERITY_TABLE.SEVERITY),  
                (DATE_RANGE.EVENT_DATE, SEVERITY_TABLE.BEGIN_WEEK, SEVERITY_TABLE.WEEKDAY, SEVERITY_TABLE.EVENT_TYPE))  
  
ORDER BY DATE_RANGE.EVENT_DATE ASC;
```

# Severity of Weather Events

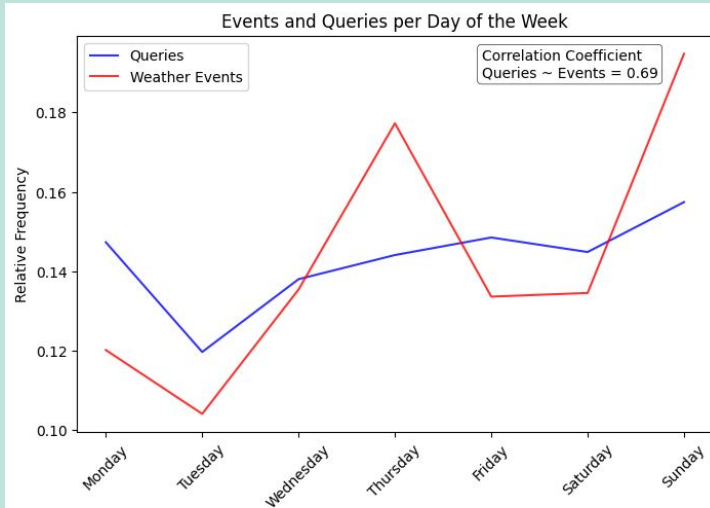


- ❑ The number of events **fluctuates heavily** over the week
- ❑ Cause: Might be due to **few extreme days**



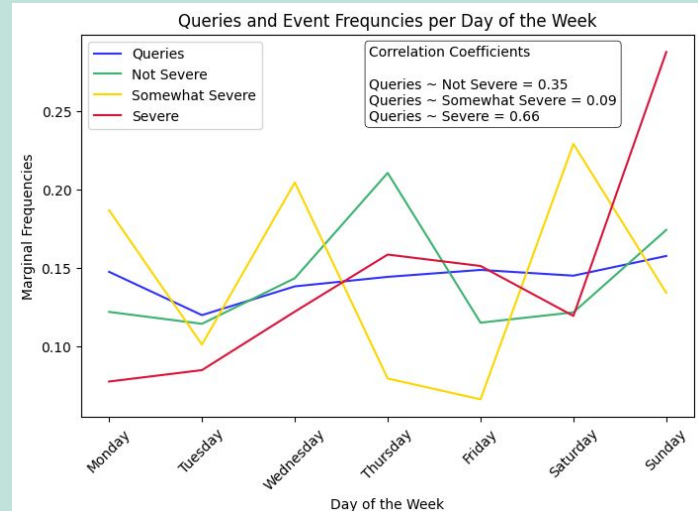
- ❑ **Extreme spikes** in weather events: Most days have few events, but occasional days experience a sharp surge

# Searches and Severity



Searches for weather events roughly follow the number of events

Strongest correlation: Severe weather events



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## Question 3:

How does the frequency of searches change during different weather events?

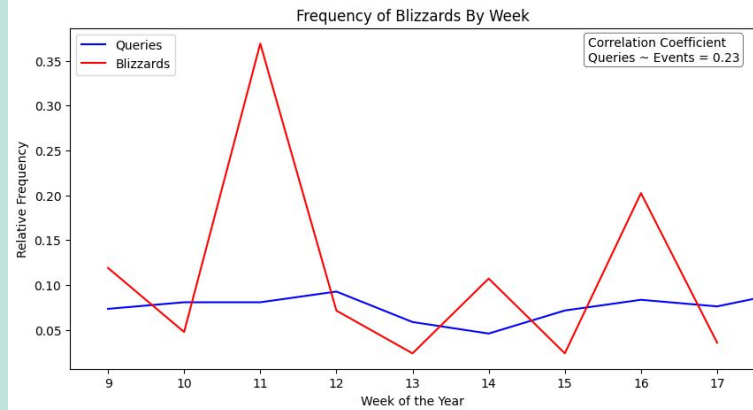


# Query



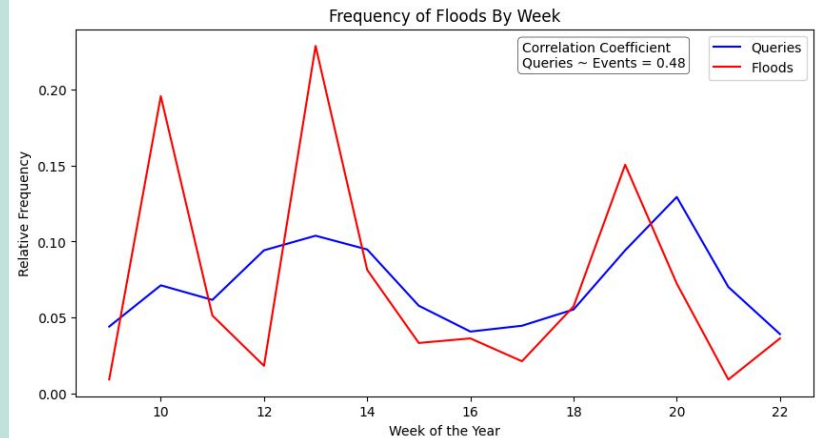
 See query before

# Blizzards and Floods

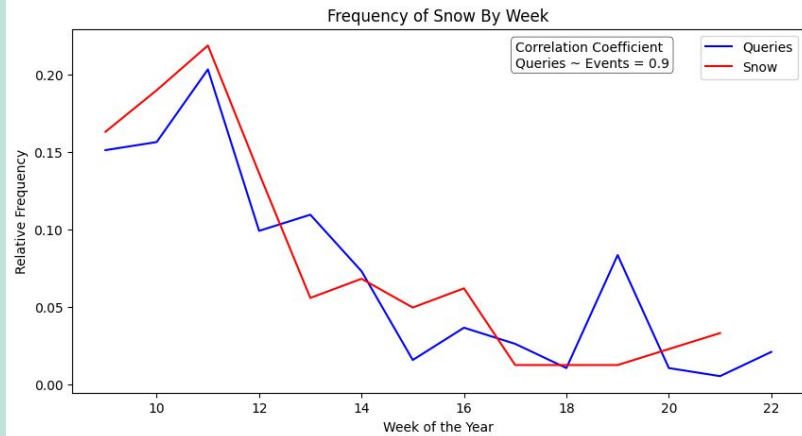


- ❏ Low correlation
- ❏ Dairy Queen had a Blizzard promotion
- ❏ Blizzard Entertainment games were very popular at the time (World of Warcraft)

❏ Clear correlation between Floods and searches for flooding

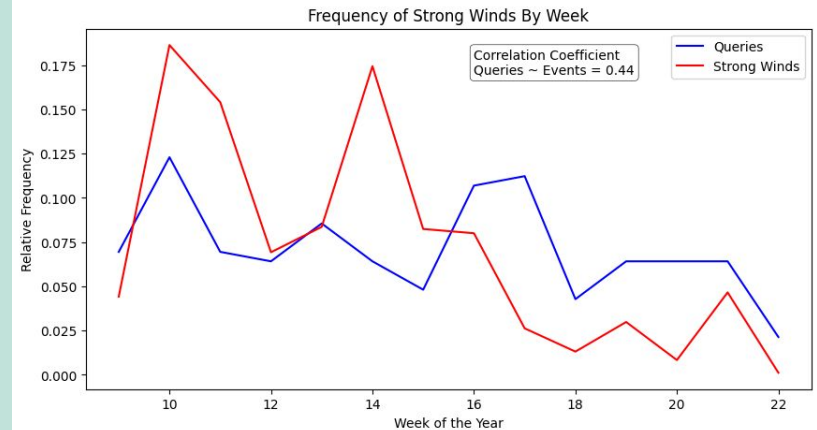


# Snowfall and Strong Wind



Strong correlation between queries for snow and actual snowy days

Only a weak to medium relationship between strong wind and searches for “strong wind”



# Digging Deeper



- ❑ We saw that tornadoes made up the majority of the severe events
- ❑ Does this correspond with weather related searches? If so, how?
- ❑ There was a series of devastating, newsworthy tornadoes during this period in the USA. (According to Wikipedia)

# Queries

## Query Frequency

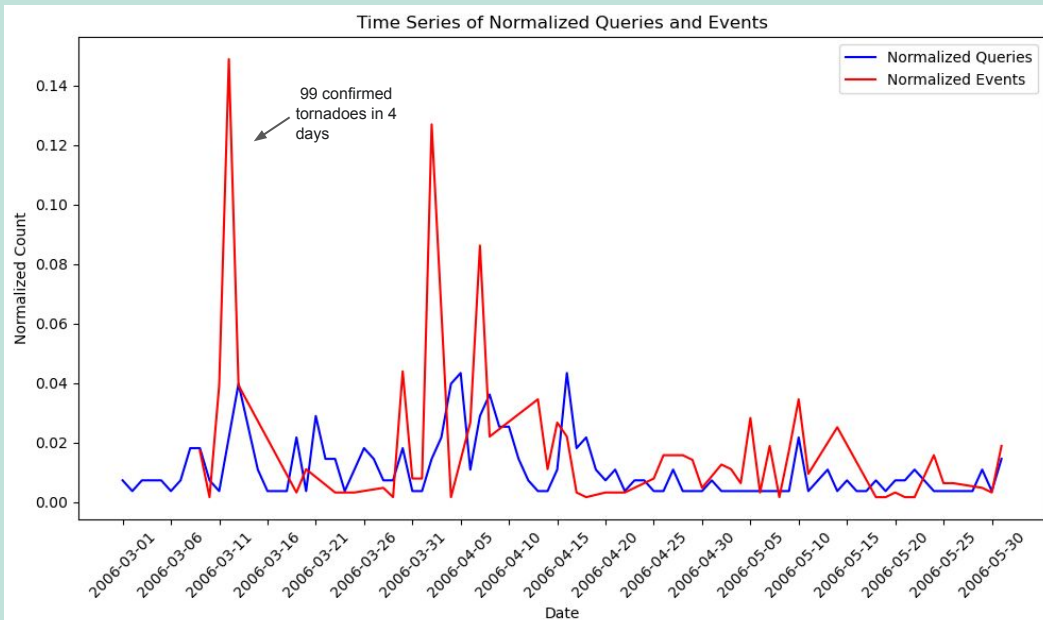
```
WITH TopURLs AS (
  SELECT URLDIM.URL
  FROM AOL_SCHEMA.FACTS
  JOIN AOL_SCHEMA.URLDIM ON AOL_SCHEMA.FACTS.URLID = AOL_SCHEMA.URLDIM.ID
  WHERE AOL_SCHEMA.FACTS.CLICK = 1
  GROUP BY URLDIM.URL
  ORDER BY COUNT(AOL_SCHEMA.FACTS.CLICK) DESC
  LIMIT 20
),
FREQCOMP AS (
  SELECT
    FACTS.ANONID,
    QUERYDIM.QUERY,
    CAST(
      CONCAT(
        '2006-',
        LPAD(CASE
          WHEN TIMEDIM."day of the year" BETWEEN 60 AND 90 THEN '03'
          WHEN TIMEDIM."day of the year" BETWEEN 91 AND 120 THEN '04'
          WHEN TIMEDIM."day of the year" BETWEEN 121 AND 151 THEN '05'
          ELSE '01'
        END, 2, '0'), '-',
        LPAD(TIMEDIM."day of the month", 2, '0'), '-',
        LPAD(TIMEDIM."hour", 2, '0'), ':',
        LPAD(TIMEDIM."minute", 2, '0'), ':',
        LPAD(TIMEDIM."second", 2, '0')
      ) AS TIMESTAMP
    ) AS time_as_datetime
  FROM
    AOL_SCHEMA.FACTS
  LEFT JOIN AOL_SCHEMA.TIMEDIM ON FACTS.TIMEID = TIMEDIM.ID
  LEFT JOIN AOL_SCHEMA.URLDIM ON FACTS.URLID = URLDIM.ID
  LEFT JOIN AOL_SCHEMA.QUERYDIM ON FACTS.QUERYID = QUERYDIM.ID
```

```
WHERE FACTS.CLICK = 1
  AND (
    URLDIM.URL IN (SELECT URL FROM TopURLs)
    OR LOWER(URLDIM.URL) LIKE '%weather%'
  )
  AND FACTS.ANONID IS NOT NULL
  AND TIMEDIM."hour" IS NOT NULL
  AND TIMEDIM."minute" IS NOT NULL
  AND TIMEDIM."second" IS NOT NULL
  AND TIMEDIM."day of the year" IS NOT NULL
),
DateRange AS (
  SELECT DATE '2006-03-01' AS EVENT_DATE
  UNION ALL SELECT DATE '2006-03-02'
  UNION ALL SELECT DATE '2006-03-03'
  ...
  UNION ALL SELECT DATE '2006-05-31'
)
SELECT
  DateRange.EVENT_DATE AS query_date,
  COALESCE(COUNT(*), 0) AS number_of_queries
FROM
  DateRange
LEFT JOIN
  FREQCOMP E
ON
  CAST(E.time_as_datetime AS DATE) = DateRange.EVENT_DATE
AND LOWER(E.QUERY) LIKE '%tornado%'
GROUP BY
  DateRange.EVENT_DATE
ORDER BY
  query_date;
```

## Tornado Frequency

```
WITH DateRange AS (
  SELECT DATE '2006-03-01' AS EVENT_DATE
  UNION ALL SELECT DATE '2006-03-02'
  ...
  UNION ALL SELECT DATE '2006-05-31'
)
SELECT
  DateRange.EVENT_DATE,
  COALESCE(COUNT(E.EPISODE_ID), 0) AS EVENT_COUNT
FROM
  DateRange
LEFT JOIN
  AOL_SCHEMA.WEATHER_EVENTS E
ON
  CAST(E.BEGIN_DATE_TIME AS DATE) = DateRange.EVENT_DATE
  AND E.EVENT_TYPE = 'Tornado'
GROUP BY
  DateRange.EVENT_DATE
ORDER BY
  DateRange.EVENT_DATE;
```

# Searches for Tornadoes vs. actual Tornadoes



- There is at least a slight relationship between the occurrence of a tornado and the frequency of queries
- Queries counted from clicks on top 20 urls or weather sites, and containing 'tornado' in query text
- Pearson's Correlation:  $\sim 0.29$



## Conclusion

- Severity of weather events seems to be a driver of search engine activity
- Lagged correlation measures could help this analysis

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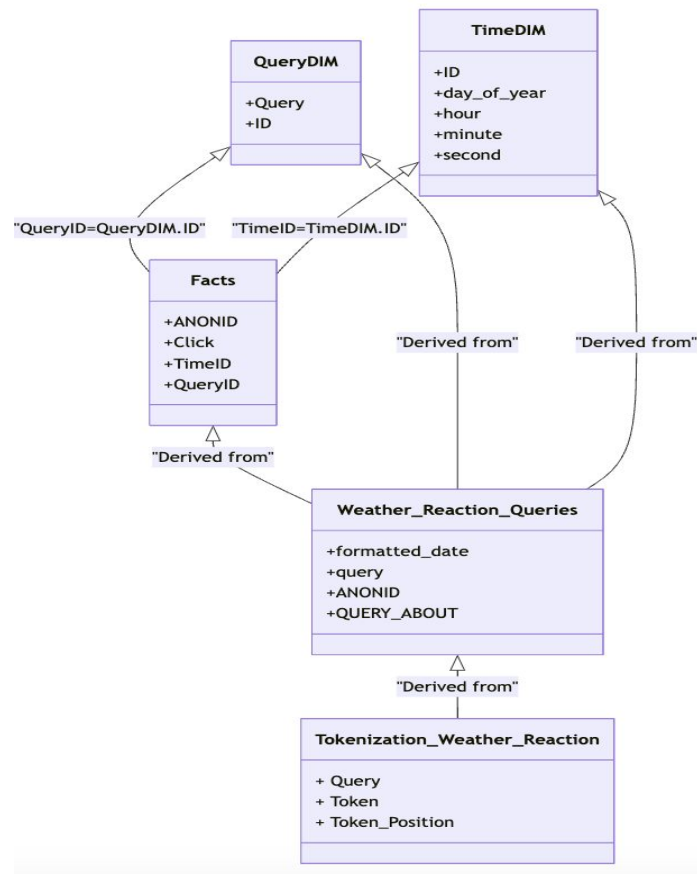
## Question 4:

**What are people most concerned about during and after tornadoes, as shown in keywords?**



# Schema and Info

- ❑ Weather Tracking and Alerts - 39,091 queries
- ❑ Damage Assessment and Recovery - 15,631 queries
- ❑ Emergency Preparedness and Safety - 7,330 queries
- ❑ Relief and Support - 7,299 queries
- ❑ Shelter and Immediate Protection - 1,980 queries



# Weather Queries Tables

```
CREATE OR REPLACE TABLE AOL_SCHEMA.Weather_Reaction_Queries AS
WITH MonthLookup AS (
    SELECT 'january' AS month_name, '01' AS month_number
    UNION ALL
    SELECT 'february', '02'
    UNION ALL
    SELECT 'march', '03'
    UNION ALL
    SELECT 'april', '04'
    ...
    SELECT 'december', '12'
),
TrimmedQuery AS (
    SELECT
        TRIM(LOWER(QUERYDIM."QUERY")) AS query_lower
    FROM AOL_SCHEMA."QUERYDIM"
),
PreparedData AS (
    SELECT
        TIMEDIM."month",
        TIMEDIM."day of the month",
        TIMEDIM."hour",
        TIMEDIM."minute",
        QUERYDIM."QUERY",
        FACTS."ANONID",
        TO_TIMESTAMP(
            '2006-' ||
            COALESCE(MonthLookup.month_number, '00') ||
            '-' ||
            LPAD(CAST(TIMEDIM."day of the month" AS VARCHAR(10)), 2, '0') ||
            '-' ||
            LPAD(CAST(TIMEDIM."hour" AS VARCHAR(2)), 2, '0') || ':' ||
            LPAD(CAST(TIMEDIM."minute" AS VARCHAR(2)), 2, '0')
        ) AS formatted_date,
        TRIM(LOWER(QUERYDIM."QUERY")) AS query_lower_trimmed
    FROM AOL_SCHEMA."TIMEDIM"
    INNER JOIN AOL_SCHEMA."QUERYDIM" ON QUERYDIM."ID" = TIMEDIM."ID"
    INNER JOIN AOL_SCHEMA."FACTS" ON FACTS."QUERYID" = QUERYDIM."ID"
    LEFT JOIN MonthLookup ON LOWER(TRIM(TIMEDIM."month")) = MonthLookup.month_name
    WHERE FACTS."CLICK" = 1
)
```

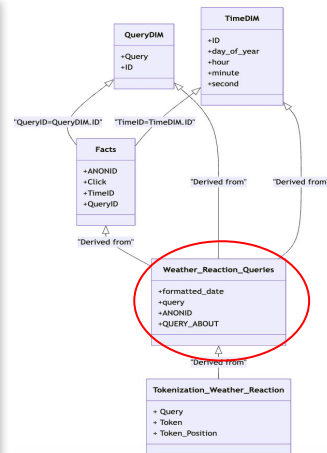
```
SELECT DISTINCT
    formatted_date,
    QUERY AS query_lower_trimmed,
    ANONID,
    CASE
        WHEN query_lower_trimmed LIKE '%shelter%'
            OR query_lower_trimmed LIKE '%safe%room%'
            OR query_lower_trimmed LIKE '%temporary%housing%'
            OR query_lower_trimmed LIKE '%housing%assistance%' THEN 'Shelter and Immediate Protection'

        WHEN query_lower_trimmed LIKE '%safety%'
            OR query_lower_trimmed LIKE '%safe%'
            ...
            OR query_lower_trimmed LIKE '%tracker%' THEN 'Emergency Preparedness and Safety'

        WHEN query_lower_trimmed LIKE '%damage%'
            OR query_lower_trimmed LIKE '%repair%'
            OR query_lower_trimmed LIKE '%insurance%' THEN 'Damage Assessment and Recovery'

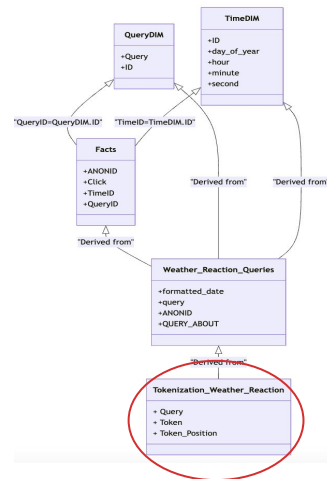
        WHEN query_lower_trimmed LIKE '%relief%'
            OR query_lower_trimmed LIKE '%volunteer%'
            ...
            OR query_lower_trimmed LIKE '%charity%' THEN 'Relief and Support'

        WHEN query_lower_trimmed LIKE '%weather%' OR
            query_lower_trimmed LIKE '%climate%' OR
            ...
            query_lower_trimmed LIKE '%weather%radar%' THEN 'Weather Tracking and Alerts'
        ELSE 'Other'
    END AS QUERY_ABOUT
FROM PreparedData
WHERE (
    query_lower_trimmed LIKE '%shelter%'
    OR query_lower_trimmed LIKE '%safety%'
    OR query_lower_trimmed LIKE '%safe%'
    OR query_lower_trimmed LIKE '%emergency%'
    OR query_lower_trimmed LIKE '%tornado%'
    OR query_lower_trimmed LIKE '%storm%'
    OR query_lower_trimmed LIKE '%damage%'
    OR query_lower_trimmed LIKE '%evacuation%'
    OR query_lower_trimmed LIKE '%survival%'
    OR query_lower_trimmed LIKE '%insurance%'
    OR query_lower_trimmed LIKE '%repair%'
    OR query_lower_trimmed LIKE '%fund%'
    OR query_lower_trimmed LIKE '%relief%'
    OR query_lower_trimmed LIKE '%warning%'
    OR query_lower_trimmed LIKE '%volunteer%'
    OR query_lower_trimmed LIKE '%donate%'
    OR query_lower_trimmed LIKE '%charity%'
    OR query_lower_trimmed LIKE '%forecast%'
    ...
    OR query_lower_trimmed LIKE '%frost%'
)
```



# Creating Tokenization Table

```
CREATE OR REPLACE TABLE AOL_SCHEMA.tokenization_weather_reaction AS
WITH limited_querydim AS (
  SELECT DISTINCT QUERY_LOWER_TRIMMED
  FROM AOL_SCHEMA.Weather_Reaction_Queries
  WHERE QUERY_LOWER_TRIMMED IS NOT NULL
    AND NOT (QUERY_LOWER_TRIMMED LIKE '%com' OR QUERY_LOWER_TRIMMED LIKE '%net' OR QUERY_LOWER_TRIMMED LIKE '%org' OR QUERY_LOWER_TRIMMED LIKE 'http%' OR
    QUERY_LOWER_TRIMMED LIKE 'www%')
),
tokenized_query AS (
  SELECT
    QUERY_LOWER_TRIMMED AS QUERY, -- Fix: Use QUERY_LOWER_TRIMMED consistently
    REGEXP_SUBSTR(
      REGEXP_REPLACE(QUERY_LOWER_TRIMMED, '[^[:alnum:]]', ''), -- Clean the query
      '^[^0-9[:space:]]+', -- Extract tokens
      1,
      LEVEL
    ) AS TOKEN,
    LEVEL AS TOKEN_POSITION
  FROM limited_querydim
  CONNECT BY PRIOR QUERY_LOWER_TRIMMED = QUERY_LOWER_TRIMMED
    AND LEVEL <= LENGTH(REGEXP_REPLACE(QUERY_LOWER_TRIMMED, '[^ ]+', '')) + 1 -- Number of words
    AND QUERY_LOWER_TRIMMED IS NOT NULL
    AND REGEXP_SUBSTR(
      REGEXP_REPLACE(QUERY_LOWER_TRIMMED, '[^[:alnum:]]', ''), -- Clean query string
      '^[^0-9[:space:]]+', -- Extract tokens
      1,
      LEVEL
    ) IS NOT NULL
)
SELECT
  QUERY,
  TOKEN,
  TOKEN_POSITION
FROM tokenized_query
WHERE TOKEN IS NOT NULL -- Exclude NULL tokens
  AND TOKEN NOT IN ('the', 'and', 'are', 'is', 'in', 'to', 'for', 'on', 'of', 'or', 'no', 'what', 'with', 'http', 'com', 'how', 'www', 'you', 'our', 'from',
  'las', 'all', 'new', 'who', 'where', 'when', 'why', 'whom', 'whose', 'which') -- Exclude common stopwords
  AND LENGTH(TOKEN) > 2 -- Exclude tokens shorter than 3 characters
ORDER BY QUERY, TOKEN_POSITION;
```



# During and After Tornado Queries

## During Tornado

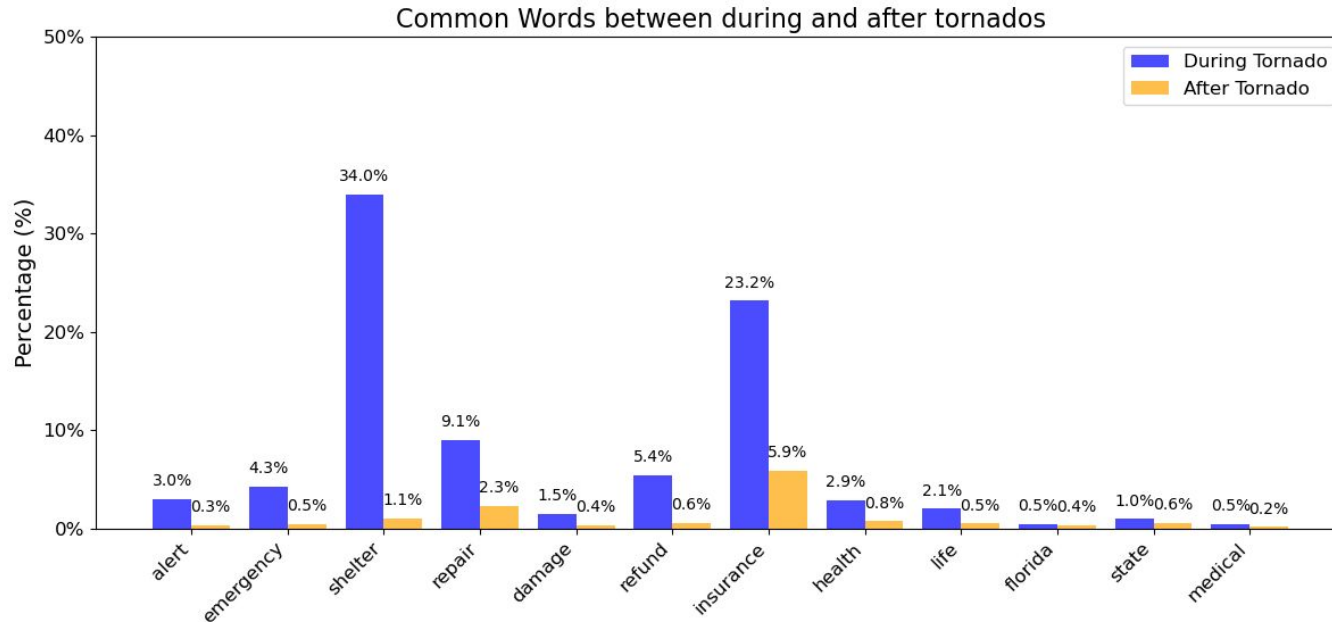
```
WITH Events_DATA AS (
  SELECT
    we.EVENT_TYPE,
    we.BEGIN_DATE_TIME,
    we.END_DATE_TIME
  FROM AOL_SCHEMA.WEATHER_EVENTS we
  WHERE we.BEGIN_DATE_TIME >= '2006-03-01 00:01:00.000000'
    AND LOWER(we.EVENT_TYPE) LIKE 'tornado'
),
Relevant_Queries AS (
  SELECT
    QUERIES_WEATHER.QUERY_LOWER_TRIMMED AS QUERY,
    QUERIES_WEATHER.FORMATTED_DATE,
    QUERIES_WEATHER.QUERY_ABOUT,
    we.EVENT_TYPE
  FROM Events_DATA we
  INNER JOIN AOL_SCHEMA.Weather_Reaction_Queries AS QUERIES_WEATHER
    ON QUERIES_WEATHER.FORMATTED_DATE BETWEEN we.BEGIN_DATE_TIME AND we.END_DATE_TIME
),
Grouped_Results AS (
  SELECT
    QUERY,
    QUERY_ABOUT,
    EVENT_TYPE,
    COUNT(*) AS query_count
  FROM Relevant_Queries
  GROUP BY GROUPING SETS (
    (QUERY, QUERY_ABOUT, EVENT_TYPE),
    (QUERY, EVENT_TYPE)
  )
),
Tokens_Queries AS (
  SELECT
    token.TOKEN,
    ex.QUERY,
    ex.QUERY_ABOUT,
    ex.EVENT_TYPE,
    ex.query_count
  FROM Grouped_Results ex
  INNER JOIN AOL_SCHEMA.tokenization_weather_reaction token
    ON ex.QUERY = token.QUERY
),
```

```
TOKEN_COUNT AS (
  SELECT
    TOKEN,
    COALESCE(QUERY_ABOUT, 'UNKNOWN') AS QUERY_ABOUT,
    SUM(query_count) AS token_count
  FROM Tokens_Queries
  GROUP BY TOKEN, QUERY_ABOUT
  HAVING SUM(query_count) > 2
  ORDER BY token_count DESC
),
TOTAL_QUERY_COUNT AS (
  SELECT
    QUERY_ABOUT,
    SUM(token_count) AS total_query_count
  FROM TOKEN_COUNT
  GROUP BY QUERY_ABOUT
),
NORMALIZED_TOKEN_COUNT AS (
  SELECT
    tc.TOKEN,
    tc.QUERY_ABOUT,
    tc.token_count,
    tqc.total_query_count,
    CASE
      WHEN tc.QUERY_ABOUT = 'UNKNOWN' THEN
        (tc.token_count * 1.0 /
         (SELECT SUM(token_count) FROM TOKEN_COUNT WHERE QUERY_ABOUT = 'UNKNOWN'))
      ELSE
        (tc.token_count * 1.0 / tqc.total_query_count)
    END AS Group_Specific_Token_Probability
  FROM TOKEN_COUNT tc
  JOIN TOTAL_QUERY_COUNT tqc
    ON tc.QUERY_ABOUT = tqc.QUERY_ABOUT
),
SELECT
  TOKEN,
  QUERY_ABOUT,
  token_count,
  total_query_count,
  Group_Specific_Token_Probability,
  Group_Specific_Token_Probability*100 AS Group_specific_Token_Percentage
FROM NORMALIZED_TOKEN_COUNT
ORDER BY QUERY_ABOUT, Group_Specific_Token_Probability DESC;
```

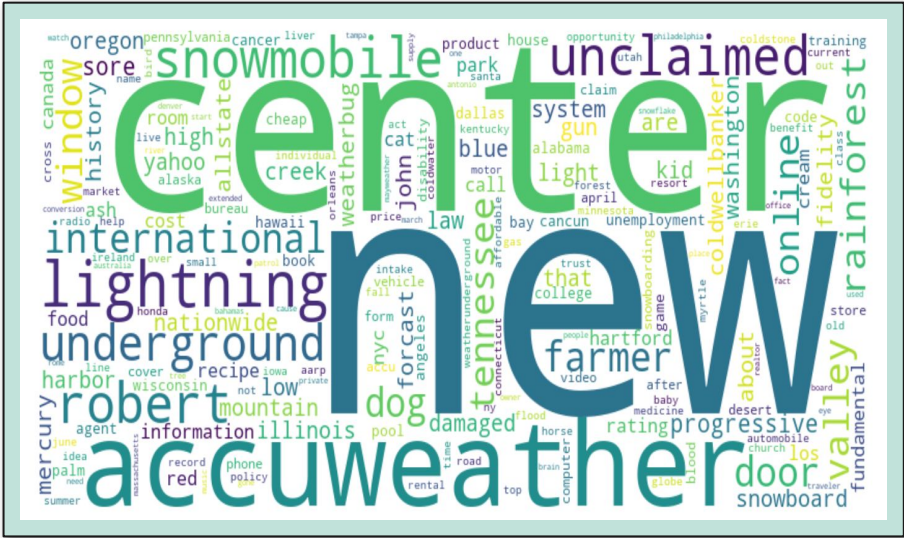
## After Tornado

```
WITH Ordered_Events AS (
  SELECT
    EVENT_TYPE,
    REGION,
    BEGIN_DATE_TIME,
    END_DATE_TIME,
    LEAD(BEGIN_DATE_TIME) OVER (ORDER BY BEGIN_DATE_TIME) AS NEXT_END_DATE_TIME
  FROM AOL_SCHEMA.WEATHER_EVENTS
  WHERE EVENT_TYPE = 'Tornado'
  ORDER BY BEGIN_DATE_TIME
),
Calculated_Events AS (
  SELECT
    EVENT_TYPE,
    BEGIN_DATE_TIME,
    END_DATE_TIME,
    ADD_MINUTES(TO_TIMESTAMP(SUBSTR(END_DATE_TIME, 1, 19)), 1) AS WINDOW_START,
    ADD_MINUTES(TO_TIMESTAMP(SUBSTR(NEXT_END_DATE_TIME, 1, 19)), -1) AS WINDOW_END
  FROM Ordered_Events
),
Window_Events AS (
  SELECT
    EVENT_TYPE,
    BEGIN_DATE_TIME,
    END_DATE_TIME,
    WINDOW_START,
    WINDOW_END
  FROM Calculated_Events
  WHERE SECONDS_BETWEEN(WINDOW_END, WINDOW_START) >= 0
),
Relevant_Queries AS (
  SELECT
    qt.QUERY_LOWER_TRIMMED AS QUERY,
    qt.QUERY_ABOUT,
    qt.FORMATTED_DATE,
    tq.EVENT_TYPE,
    tq.BEGIN_DATE_TIME,
    tq.END_DATE_TIME,
    tq.WINDOW_START,
    tq.WINDOW_END
  FROM Window_Events tq
  INNER JOIN AOL_SCHEMA.Weather_Reaction_Queries qt
    ON qt.FORMATTED_DATE BETWEEN tq.WINDOW_START AND tq.WINDOW_END
),
```

# Commonly Searched Keywords during and after Tornadoes

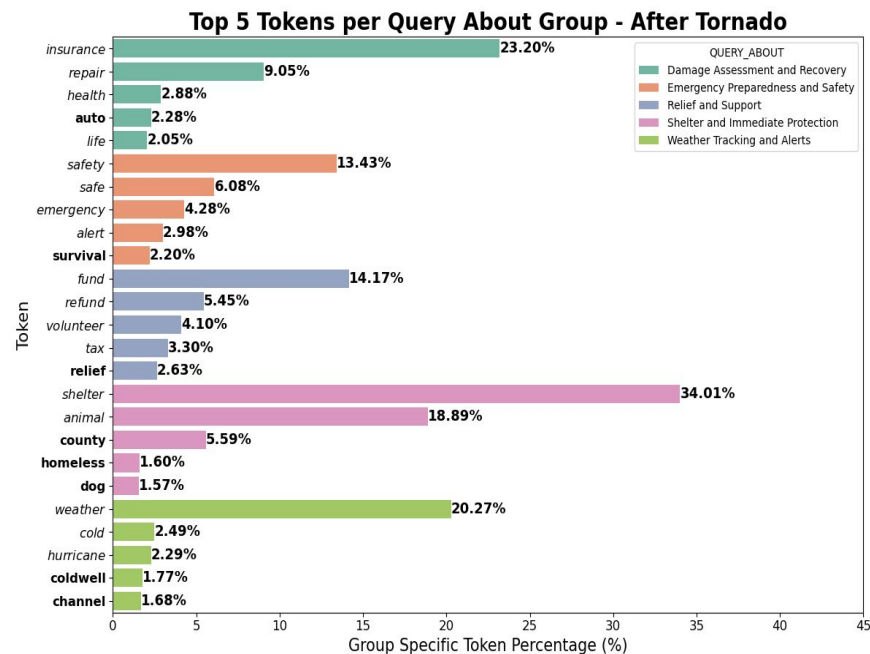
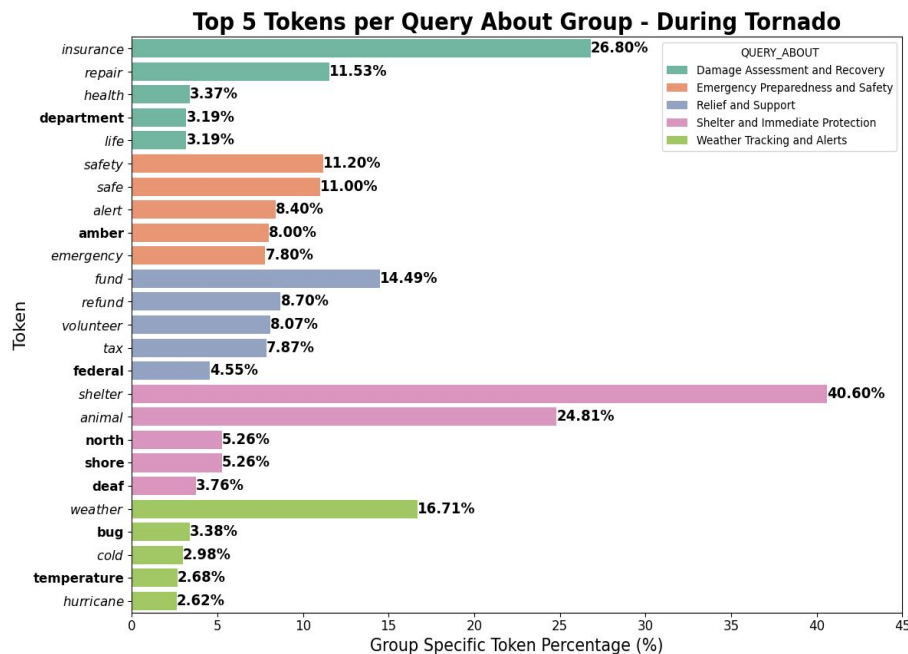


- ❑ **During Tornado**, the focus is on immediate response, emergency services, and damage repair, with terms like **shelter**, **repair**, **insurance**, and **alert**.



- ❑ **After Tornado:** Focuses on recovery with terms like "accuweather" for weather monitoring

# Relevant Keywords before and after Tornadoes



# Conclusion



- ❏ Terms like **insurance**, **safety**, **shelter** are searched for more during tornadoes which might indicate an enhanced focus on **security**
- ❏ Users search for **alert related sites** more during tornadoes than after tornadoes



---

## Question 5:

Do users behave more anxiously (click faster) during disasters\*?

\*Specifically during tornadoes

# Interclick Times



**Theory:** People will click on the next link faster during Tornadoes

**Approach:** Create a new measure as the time between clicking on links for each user

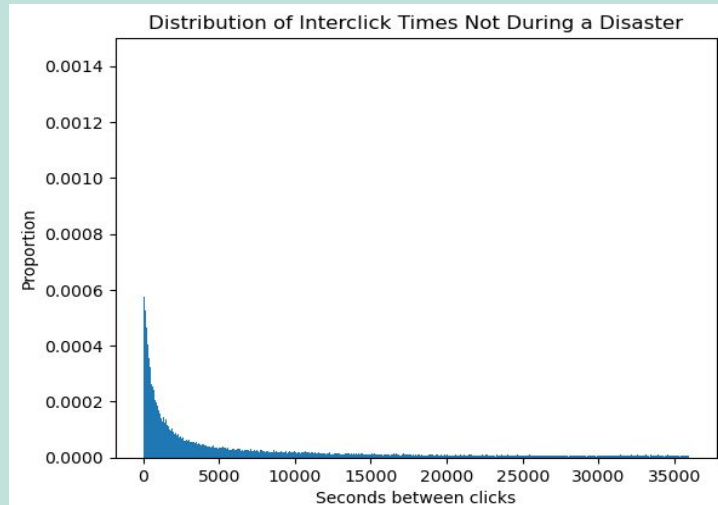
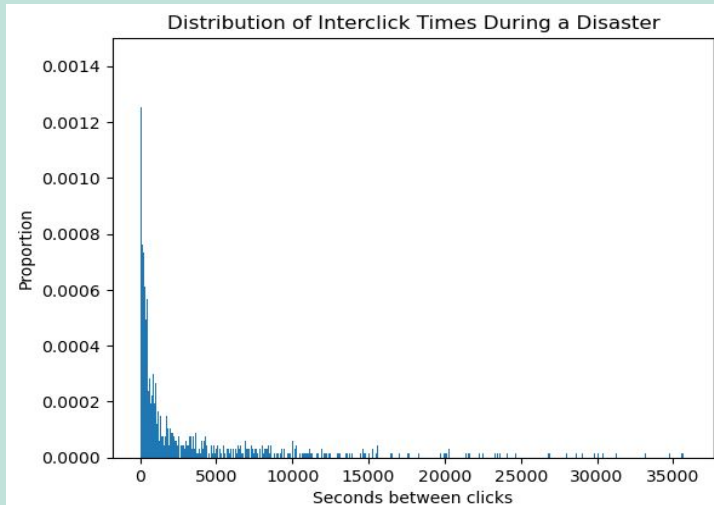
# Creating a Table & Base Query

```
CREATE TABLE AOL_SCHEMA.INTERARRIVAL_TIMES AS
SELECT
  FACTS.ANONID,
  CAST(
    CONCAT(
      '2006-'
      LPAD(CASE
        WHEN TIMEDIM.[day of the year] BETWEEN 60 AND 90 THEN '03'
        WHEN TIMEDIM.[day of the year] BETWEEN 91 AND 120 THEN '04'
        WHEN TIMEDIM.[day of the year] BETWEEN 121 AND 151 THEN '05'
        ELSE '01'
      END, 2, '0'), '-'
      LPAD(TIMEDIM.[day of the month], 2, '0'), '-',
      LPAD(TIMEDIM.[hour], 2, '0'), ':',
      LPAD(TIMEDIM.[minute], 2, '0'), ':',
      LPAD(TIMEDIM.[second], 2, '0')
    ) AS TIMESTAMP) AS time_as_datetime
FROM
  AOL_SCHEMA.FACTS LEFT JOIN AOL_SCHEMA.TIMEDIM ON FACTS.TIMEID = TIMEDIM.ID
  LEFT JOIN AOL_SCHEMA.URLDIM ON FACTS.URLID = URLDIM.ID
WHERE FACTS.CLICK = 1
  AND URLDIM.URL IN (
    SELECT URLDIM.URL
    FROM AOL_SCHEMA.FACTS
    JOIN AOL_SCHEMA.URLDIM ON AOL_SCHEMA.FACTS.URLID = AOL_SCHEMA.URLDIM.ID
    WHERE AOL_SCHEMA.FACTS.CLICK = 1
    GROUP BY URLDIM.URL
    ORDER BY COUNT(AOL_SCHEMA.FACTS.CLICK) DESC
    LIMIT 20
  )
AND FACTS.ANONID IS NOT NULL
AND TIMEDIM.[hour] IS NOT NULL
AND TIMEDIM.[minute] IS NOT NULL
AND TIMEDIM.[second] IS NOT NULL
AND TIMEDIM.[day of the year] IS NOT NULL
```

```
SELECT
  T1.ANONID,
  T1.TIME_AS_DATETIME,
  COALESCE(LAG(TIME_AS_DATETIME) OVER (PARTITION BY ANONID ORDER BY TIME_AS_DATETIME), TIME_AS_DATETIME) AS LaggedDateTime,
  SECONDS BETWEEN (T1.TIME_AS_DATETIME, COALESCE(LAG(TIME_AS_DATETIME) OVER (PARTITION BY ANONID ORDER BY TIME_AS_DATETIME), TIME_AS_DATETIME)) AS
Seconds_Difference,
  MINUTES BETWEEN (T1.TIME_AS_DATETIME, COALESCE(LAG(TIME_AS_DATETIME) OVER (PARTITION BY ANONID ORDER BY TIME_AS_DATETIME), TIME_AS_DATETIME)) AS
Minutes_Difference
FROM
  AOL_SCHEMA.INTERARRIVAL_TIMES as T1
WHERE
  T1.ANONID IN (
    SELECT T2.ANONID
    FROM AOL_SCHEMA.INTERARRIVAL_TIMES as T2
    GROUP BY T2.ANONID
    HAVING COUNT(T2.ANONID) >= 10
  )
  AND EXISTS(
    SELECT 1
    FROM AOL_SCHEMA.WEATHER_EVENTS as T3
    WHERE
      (T1.TIME_AS_DATETIME BETWEEN T3.BEGIN_DATE_TIME AND T3.END_DATE_TIME)
      AND (T3.EVENT_TYPE = 'Tornado')
  )
ORDER BY
  T1.ANONID,
  T1.TIME_AS_DATETIME
```

- ❏ The query to obtain the interclick times not occurring during a tornado is only modified in the exists statement where clause.

# Times between Clicks



- ❑ Higher spike for short interclick times during tornadoes
- ❑ Visual comparison is insufficient  $\Rightarrow$  Statistical test

# Statistical Test



We use a **T-Test** assuming unequal variances with a **significance level** of **0.05**

$H_0$ : There is **no difference in mean interclick time** between those occurring during and those not occurring during a natural disaster.

$H_1$ : There **is a difference in mean interclick time** between those occurring during and those not occurring during a natural disaster.

## T-Test Results:

Test Statistic: -44.5

P-Value: 0.0000\*

\*Below Numerical Precision

# Conclusion



- ❑ P-value < 0.05  $\Rightarrow$  **reject  $H_0$**
- ❑ The data suggests there is a **statistically significant difference** in mean time between clicks when there is a tornado compared to when there is none

## Additional Insight:

- ❑ The number of clicks in a period of time could be modeled as a Poisson process
- ❑ This would allow you to construct data-driven query engine traffic simulations

---

# Summary

# Summary of Findings



1. Damages were concentrated in single states
2. The majority of weather events: Not severe and cold or wind related
3. Search trends for weather events followed actual events, especially severe ones
4. Searches for keywords such as '*Shelter*' or '*Insurance*' see a significant increase during tornadoes.
5. Users clicked on links faster on average during tornadoes





**Thank you for your attention!**

---

**Question (Bonus):**

**Which domains were most clicked during weather events that occurred in different regions?**

# Query

Most clicked domains or URLs and matched by time to specific weather events and regions where they occurred

```
WITH ClickedDomains AS (
  SELECT
    AOL_SCHEMA.WEATHER_EVENTS.REGION AS REGION,
    AOL_SCHEMA.WEATHER_EVENTS.EVENT_TYPE AS EVENT_TYPE,
    AOL_SCHEMA.WEATHER_EVENTS.BEGIN_DATE_TIME AS BEGIN_DATE_TIME,
    AOL_SCHEMA.URLDIM.THISDOMAIN AS THISDOMAIN,
    AOL_SCHEMA.URLDIM.URL AS URL,
    COUNT(AOL_SCHEMA.FACTS.URLID) AS CLICK_COUNT
  FROM
    AOL_SCHEMA.WEATHER_EVENTS
  JOIN
    AOL_SCHEMA.FACTS
    ON AOL_SCHEMA.WEATHER_EVENTS.BEGIN_DAY = AOL_SCHEMA.FACTS.TIMEID
  JOIN
    AOL_SCHEMA.URLDIM
    ON AOL_SCHEMA.FACTS.URLID = AOL_SCHEMA.URLDIM.ID
  WHERE
    AOL_SCHEMA.FACTS.CLICK = TRUE
    AND (AOL_SCHEMA.URLDIM.THISDOMAIN IS NOT NULL OR AOL_SCHEMA.URLDIM.URL IS NOT NULL)
    AND AOL_SCHEMA.WEATHER_EVENTS.BEGIN_DATE_TIME BETWEEN '2006-03-01 00:00:00' AND '2006-05-31 23:59:59'
  GROUP BY ROLLUP (
    AOL_SCHEMA.WEATHER_EVENTS.REGION,
    AOL_SCHEMA.WEATHER_EVENTS.EVENT_TYPE,
    AOL_SCHEMA.WEATHER_EVENTS.BEGIN_DATE_TIME,
    AOL_SCHEMA.URLDIM.THISDOMAIN,
    AOL_SCHEMA.URLDIM.URL
  )
),
```

```
RankedDomains AS (
  SELECT
    REGION,
    EVENT_TYPE,
    BEGIN_DATE_TIME,
    THISDOMAIN,
    URL,
    CLICK_COUNT,
    ROW_NUMBER() OVER (
      PARTITION BY REGION, EVENT_TYPE
      ORDER BY CLICK_COUNT DESC
    ) AS RANK
  FROM
    ClickedDomains
  WHERE
    THISDOMAIN IS NOT NULL OR URL IS NOT NULL
)
SELECT
  REGION,
  EVENT_TYPE,
  BEGIN_DATE_TIME,
  THISDOMAIN,
  URL,
  CLICK_COUNT
FROM
  RankedDomains
WHERE
  RANK = 1
ORDER BY
  REGION,
  EVENT_TYPE,
  BEGIN_DATE_TIME;
```



## Result

	REGION	EVENT_TYPE	BEGIN_DATE_TIME	THISDOMAIN	URL	CLICK_COUNT
0	Alabama	Flash Flood	2006-03-20 18:45:00.000000	nau	http://www.nau.edu	3
1	Alabama	Funnel Cloud	2006-03-20 17:55:00.000000	nau	http://www.nau.edu	3
2	Alabama	Hail	2006-04-20 17:08:00.000000	nau	http://www.nau.edu	6
3	Alabama	Lightning	2006-04-18 18:10:00.000000	citysearch	http://pittsburgh.citysearch.com	1
4	Alabama	Strong Wind	2006-03-09 14:15:00.000000	ca	http://gocalif.ca.gov	1
...	...	...	...	...	...	...
487	Wyoming	Heavy Snow	2006-05-09 04:00:00.000000	ca	http://gocalif.ca.gov	2
488	Wyoming	Lightning	2006-05-08 14:10:00.000000	ebay.co	http://www.ebay.co.uk	1
489	Wyoming	Thunderstorm Wind	2006-05-26 16:39:00.000000	yahoo	http://mail.yahoo.com	1
490	Wyoming	Wildfire	2006-04-10 09:00:00.000000	bilkent.edu	http://web.bilkent.edu.tr	1
491	Wyoming	Winter Storm	2006-04-24 01:00:00.000000	sharesong	http://www.sharesong.org	4

492 rows × 6 columns

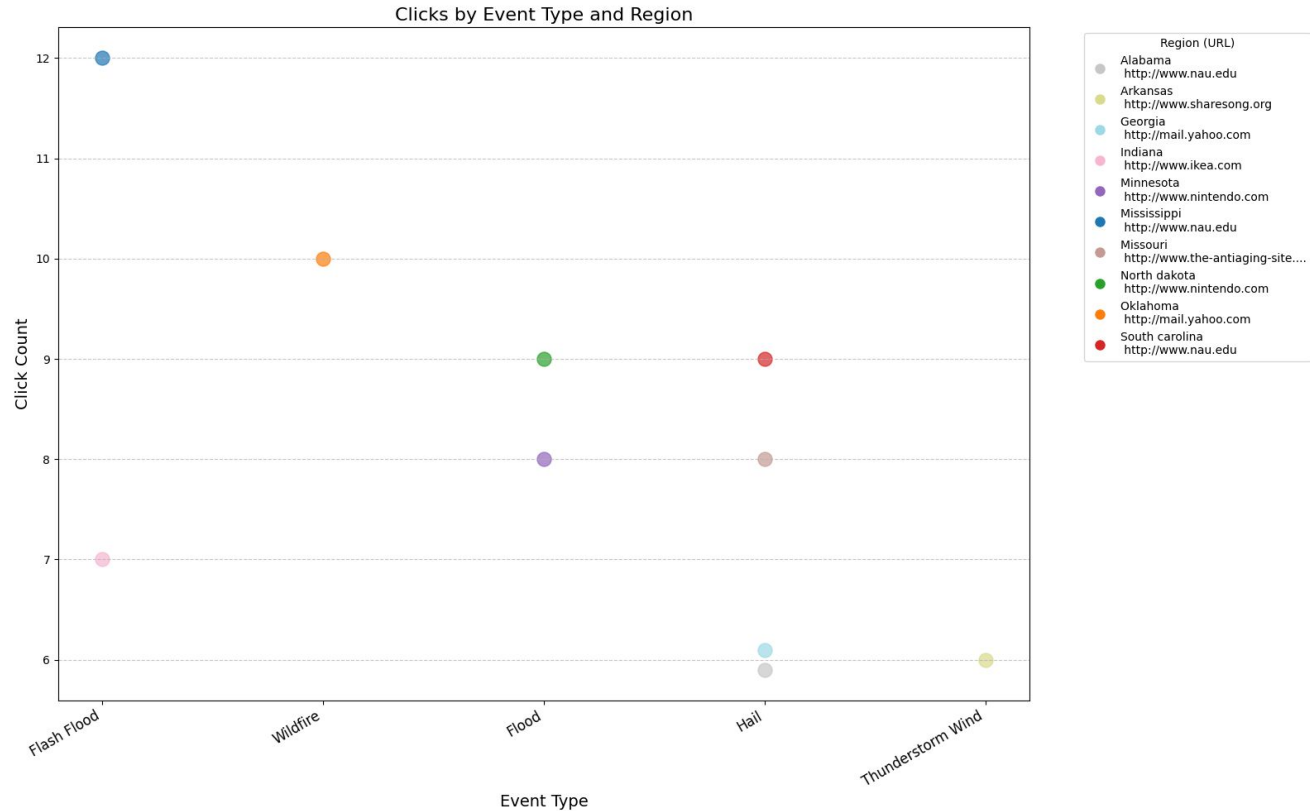
# Query

## Top 10 most clicked URLs during severe weather events

```
WITH ClickedDomains AS (  
  SELECT  
    AOL_SCHEMA.WEATHER_EVENTS.REGION AS REGION,  
    AOL_SCHEMA.WEATHER_EVENTS.EVENT_TYPE AS EVENT_TYPE,  
    AOL_SCHEMA.WEATHER_EVENTS.BEGIN_DATE_TIME AS BEGIN_DATE_TIME,  
    AOL_SCHEMA.URLDIM.THISDOMAIN AS THISDOMAIN,  
    AOL_SCHEMA.URLDIM.URL AS URL,  
    COUNT(AOL_SCHEMA.FACTS.URLID) AS CLICK_COUNT  
  FROM  
    AOL_SCHEMA.WEATHER_EVENTS  
  JOIN  
    AOL_SCHEMA.FACTS  
    ON AOL_SCHEMA.WEATHER_EVENTS.BEGIN_DAY = AOL_SCHEMA.FACTS.TIMEID  
  JOIN  
    AOL_SCHEMA.URLDIM  
    ON AOL_SCHEMA.FACTS.URLID = AOL_SCHEMA.URLDIM.ID  
  WHERE  
    AOL_SCHEMA.FACTS.CLICK = TRUE  
    AND (AOL_SCHEMA.URLDIM.THISDOMAIN IS NOT NULL OR AOL_SCHEMA.URLDIM.URL IS NOT NULL)  
    AND AOL_SCHEMA.WEATHER_EVENTS.BEGIN_DATE_TIME BETWEEN '2006-03-01 00:00:00' AND '2006-05-31 23:59:59'  
  GROUP BY  
    AOL_SCHEMA.WEATHER_EVENTS.REGION,  
    AOL_SCHEMA.WEATHER_EVENTS.EVENT_TYPE,  
    AOL_SCHEMA.WEATHER_EVENTS.BEGIN_DATE_TIME,  
    AOL_SCHEMA.URLDIM.THISDOMAIN,  
    AOL_SCHEMA.URLDIM.URL  
)
```

```
RankedDomains AS (  
  SELECT  
    REGION,  
    EVENT_TYPE,  
    BEGIN_DATE_TIME,  
    THISDOMAIN,  
    URL,  
    CLICK_COUNT,  
    ROW_NUMBER() OVER (  
      PARTITION BY REGION  
      ORDER BY CLICK_COUNT DESC, BEGIN_DATE_TIME ASC  
    ) AS RANK  
  FROM  
    ClickedDomains  
)  
SELECT  
  REGION,  
  EVENT_TYPE,  
  BEGIN_DATE_TIME,  
  THISDOMAIN,  
  URL,  
  CLICK_COUNT  
FROM  
  RankedDomains  
WHERE  
  RANK = 1  
ORDER BY CLICK_COUNT DESC  
LIMIT 10;
```

# Visualization





## Conclusion

During severe weather events, people are staying at home and use mostly entertainment or education websites

Specific weather events (like Wildfire or Flash Flood) are correlated with spikes in clicks

---

# Appendix





## **Diving into the queries: A Closer Look**


This section provides an in-depth analysis of how SQL queries were crafted to answer key questions using ROLAP techniques.

"Ever wondered how SQL queries bring multidimensional data to life?"

## Query 1

```
WITH NewWeatherData AS (
  SELECT
    MONTH(BEGIN_DATE_TIME) AS BEGIN_MON,
    REGION,
    CASE
      -- West Region
      WHEN STATE_FIPS IN ('02', '04', '06', '08', '15', '16', '30', '32', '35', '41', '49', '53', '56') THEN 'West'
      -- Central Region
      WHEN STATE_FIPS IN ('05', '17', '18', '19', '20', '26', '27', '29', '31', '38', '39', '46', '48', '55') THEN 'Central'
      -- East Region
      WHEN STATE_FIPS IN ('01', '09', '10', '11', '12', '13', '21', '22', '23', '24', '25', '28', '33', '34', '36', '37', '40', '42', '44', '45', '47', '50', '51', '54') THEN 'East'
      ELSE 'Unknown'
    END AS TRISECTION,
    COALESCE(INJURIES_DIRECT, 0) + COALESCE(INJURIES_INDIRECT, 0) + COALESCE(DEATHS_DIRECT, 0) + COALESCE(DEATHS_INDIRECT, 0) AS HUMAN_DAMAGE,
    COALESCE(DAMAGE_PROPERTY, 0) + COALESCE(DAMAGE_CROPS, 0) AS NON_HUMAN_DAMAGE
  FROM
    AOL_SCHEMA.WEATHER_EVENTS
  WHERE
    MONTH(BEGIN_DATE_TIME) >= 3.0
)
SELECT
  BEGIN_MON,
  REGION,
  TRISECTION,
  SUM(HUMAN_DAMAGE) AS TOTAL_HUMAN_DAMAGE,
  SUM(NON_HUMAN_DAMAGE) AS TOTAL_NON_HUMAN_DAMAGE
FROM
  NewWeatherData
GROUP BY
  CUBE(BEGIN_MON, REGION, TRISECTION)
HAVING
  SUM(HUMAN_DAMAGE) > 0
  AND SUM(NON_HUMAN_DAMAGE) > 0
ORDER BY
  BEGIN_MON,
  TRISECTION,
  REGION;
```

Key operations utilized: Cube



**Working of the query:** Uses the CUBE operation to aggregate property and personnel damage by states, regions, and the starting months of natural disasters.

**Output:**

	BEGIN_MON	REGION	TRISECTION	TOTAL_HUMAN_DAMAGE	TOTAL_NON_HUMAN_DAMAGE
0	3.0	Arkansas	Central	19	175000
1	3.0	Illinois	Central	39	300000
2	3.0	Indiana	Central	3	163000
3	3.0	Iowa	Central	3	220000
4	3.0	Kansas	Central	5	296000
...	...	...	...	...	...
257	NaN	Virginia	NaN	3	215000
258	NaN	Washington	NaN	3	49000
259	NaN	West virginia	NaN	3	104000
260	NaN	Wisconsin	NaN	7	403000
261	NaN	NaN	NaN	1173	549989300

## Questions (2/3)<sub>a</sub>

### Key Operators:

- ROLLUP
- RANK
- PARTITION BY

```
WITH SEVERITY_TABLE AS(  
    SELECT  
        EVENT_ID,  
        EVENT_TYPE,  
        BEGIN_DATE_TIME,  
        CASE  
            WHEN WEATHER_EVENTS.EVENT_TYPE IN ('Blizzard', 'Tornado', 'Wildfire', 'Avalanche', 'Funnel Cloud', 'Waterspout',  
'Debris Flow') THEN 'Severe'  
            WHEN WEATHER_EVENTS.EVENT_TYPE IN ('Coastal Flood', 'Flash Flood', 'Flood', 'Drought', 'Dust Devil', 'Dust Storm',  
'Storm Surge/Tide', 'Ice Storm', 'Winter Storm') THEN 'Somewhat Severe'  
            WHEN WEATHER_EVENTS.EVENT_TYPE IN ('Cold/Wind Chill', 'Frost/Freeze', 'Heat', 'Heavy Rain', 'Heavy Snow', 'High  
Wind', 'Strong Wind', 'Thunderstorm Wind', 'Winter Weather', 'Lightning', 'Marine High Wind', 'Marine Thunderstorm Wind',  
'Sleet', 'WINTER WEATHER', 'High Surf', 'Marine Hail', 'Rip Current', 'Lake-Effect Snow', 'Dense Fog') THEN 'Not Severe'  
            ELSE 'Unclassified'  
        END AS SEVERITY  
    FROM AOL_SCHEMA.WEATHER_EVENTS  
)  
AGG_EVENTS AS(  
    SELECT  
        SEVERITY,  
        EVENT_TYPE,  
        COALESCE(COUNT(EVENT_ID),0) AS FREQ  
    FROM SEVERITY_TABLE  
    GROUP BY ROLLUP(SEVERITY, EVENT_TYPE)  
    SELECT  
        SEVERITY,  
        EVENT_TYPE,  
        FREQ,  
        RANK() OVER(PARTITION BY SEVERITY ORDER BY FREQ DESC) as RANKING  
    FROM AGG_EVENTS  
);
```

## Output

The total amount for each EVENT\_TYPE is aggregated. Then hierarchically grouped by SEVERITY. The EVENT\_TYPES in each SEVERITY grouping are then ranked from the most to least frequent events.

	SEVERITY	EVENT_TYPE	FREQ	RANKING
0	Not Severe	NaN	20832	1
1	Not Severe	Hail	9843	2
2	Not Severe	Thunderstorm Wind	4844	3
3	Not Severe	High Wind	1498	4
4	Not Severe	Heavy Snow	999	5
5	Not Severe	Strong Wind	738	6
6	Not Severe	Winter Weather	647	7
7	Not Severe	WINTER WEATHER	421	8
8	Not Severe	Marine Thunderstorm Wind	344	9
9	Not Severe	Cold/Wind Chill	339	10
10	Not Severe	Dense Fog	265	11
11	Not Severe	Heavy Rain	258	12
12	Not Severe	Lightning	235	13
13	Not Severe	High Surf	157	14
14	Not Severe	Frost/Freeze	125	15
15	Not Severe	Heat	66	16
16	Not Severe	Lake-Effect Snow	21	17
17	Not Severe	Marine Hail	20	18
18	Not Severe	Marine High Wind	6	19
19	Not Severe	Rip Current	5	20
20	Not Severe	Sleet	1	21

21	Severe	NaN	1326	1
22	Severe	Tornado	705	2
23	Severe	Wildfire	191	3
24	Severe	Funnel Cloud	166	4
25	Severe	Blizzard	139	5
26	Severe	Waterspout	52	6
27	Severe	Avalanche	41	7
28	Severe	Debris Flow	32	8
29	Somewhat Severe	NaN	3576	1
30	Somewhat Severe	Drought	1213	2
31	Somewhat Severe	Winter Storm	1097	3
32	Somewhat Severe	Flash Flood	599	4
33	Somewhat Severe	Flood	516	5
34	Somewhat Severe	Coastal Flood	67	6
35	Somewhat Severe	Ice Storm	48	7
36	Somewhat Severe	Dust Storm	19	8
37	Somewhat Severe	Storm Surge/Tide	15	9
38	Somewhat Severe	Dust Devil	2	10
39	NaN	NaN	25734	1

# Questions (2/3)<sub>b</sub>

## Key Operators:

- ROLLUP

```
WITH DATE_RANGE AS (
  SELECT DATE '2006-03-01' AS EVENT_DATE
  UNION ALL SELECT DATE '2006-03-02'
  .
  .
  UNION ALL SELECT DATE '2006-05-31'
),
SEVERITY_TABLE AS(
SELECT
  EVENT_TYPE,
  EVENT_ID,
  CAST(WEATHER_EVENTS.BEGIN_DATE_TIME AS DATE) AS BEGIN_DATE,
  WEEK(WEATHER_EVENTS.BEGIN_DATE_TIME) AS BEGIN_WEEK,
  (MOD(CAST(CAST(WEATHER_EVENTS.BEGIN_DATE_TIME AS DATE) - CAST('2006-01-01' AS DATE) AS INTEGER) + 6, 7) + 1) AS WEEKDAY,
  CASE
    WHEN WEATHER_EVENTS.EVENT_TYPE IN ('Blizzard', 'Tornado', 'Wildfire', 'Avalanche', 'Funnel Cloud', 'Waterspout') THEN 'Severe'

    WHEN WEATHER_EVENTS.EVENT_TYPE IN ('Coastal Flood', 'Flash Flood', 'Flood', 'Drought', 'Dust, Devil',
    'Dust Storm', 'Storm Surge/Tide') THEN 'Somewhat Severe'

    WHEN WEATHER_EVENTS.EVENT_TYPE IN ('Cold/Wind Chill', 'Frost/Freeze', 'Heat', 'Heavy Rain', 'Heavy Snow', 'Hail', 'High Wind', 'Strong Wind', 'Thunderstorm Wind',
    'Winter Weather', 'Lightning', 'Marine High Wind', 'Marine Thunderstorm Wind', 'Sleet', 'WINTER WEATHER', '
    Winter Storm') THEN 'Not Severe'

    ELSE 'Unclassified'
  END AS SEVERITY
FROM AOL_SCHEMA.WEATHER_EVENTS
)

SELECT
  DATE_RANGE.EVENT_DATE,
  SEVERITY_TABLE.BEGIN_WEEK,
  SEVERITY_TABLE.WEEKDAY,
  SEVERITY_TABLE.SEVERITY,
  SEVERITY_TABLE.EVENT_TYPE,
  COALESCE(COUNT(SEVERITY_TABLE.EVENT_ID), 0) AS FREQ
FROM DATE_RANGE

LEFT JOIN SEVERITY_TABLE
ON DATE_RANGE.EVENT_DATE = SEVERITY_TABLE.BEGIN_DATE

GROUP BY ROLLUP((DATE_RANGE.EVENT_DATE, SEVERITY_TABLE.BEGIN_WEEK, SEVERITY_TABLE.WEEKDAY, SEVERITY_TABLE.SEVERITY),\
  (DATE_RANGE.EVENT_DATE, SEVERITY_TABLE.BEGIN_WEEK, SEVERITY_TABLE.WEEKDAY, SEVERITY_TABLE.EVENT_TYPE))

ORDER BY DATE_RANGE.EVENT_DATE ASC;
```



## Output

Again, the total occurrences of each EVENT\_TYPE is aggregated then hierarchically grouped by severity. Additionally, each data point has the date, week, and day of the week that the event occurred on. This allowed us to analyze all EVENT\_TYPES and SEVERITY groups by any relevant time dimension.

	EVENT_DATE	BEGIN_WEEK	WEEKDAY	SEVERITY	EVENT_TYPE	FREQ
0	2006-03-01	9.0	3.0	Not Severe	Heavy Snow	20
1	2006-03-01	9.0	3.0	Not Severe	Winter Weather	5
2	2006-03-01	9.0	3.0	Not Severe	High Wind	16
3	2006-03-01	9.0	3.0	Not Severe	Strong Wind	1
4	2006-03-01	9.0	3.0	Not Severe	Cold/Wind Chill	3
...	...	...	...	...	...	...
1262	2006-05-31	22.0	3.0	Not Severe	NaN	149
1263	2006-05-31	22.0	3.0	Somewhat Severe	NaN	22
1264	2006-05-31	22.0	3.0	Severe	NaN	14
1265	2006-05-31	22.0	3.0	Unclassified	NaN	95
1266	NaN	NaN	NaN	NaN	NaN	19545

## Questions (2/3)<sub>b</sub>

This SQL query was used to help generate the graphs on slides **23**, **26**, and **27**. Here, we are joining only rows where the AOL query contains the keyword 'weather'. For other graphs, the keyword was changed to 'blizzard', 'snow', 'wind', and 'flood'. In the query for blizzards, we had to drop the condition that the URL also be weather related. Otherwise the dataset was too small to use. However, this also introduced many non-relevant AOL queries to the data, resulting in low-quality data.

```
WITH DATE_RANGE AS (
  SELECT DATE '2006-03-01' AS EVENT_DATE
  UNION ALL SELECT DATE '2006-03-02'
  .
  .
  .
  UNION ALL SELECT DATE '2006-05-31'
),
QUERY_FREQ AS (
  SELECT
    QUERYDIM.QUERY,
    TIMEDIM.[calender week],
    TIMEDIM.[day of the week],
    CAST (TO_TIMESTAMP(
      CONCAT(
        TIMEDIM.[year], '-',
        CASE
          WHEN CAST(TIMEDIM.[month] AS CHAR(5)) = 'march' THEN '03'
          WHEN CAST(TIMEDIM.[month] AS CHAR(5)) = 'april' THEN '04'
          WHEN CAST(TIMEDIM.[month] AS CHAR(5)) = 'may' THEN '05'
          ELSE 'NULL'
        END
        , '-', LPAD(TIMEDIM.[day of the month], 2, '0')),
      'YYYY-MM-DD'
    ) AS DATE) AS YMD_TIMESTAMP

  FROM AOL_SCHEMA.FACTS
  LEFT JOIN AOL_SCHEMA.TIMEDIM ON FACTS.TIMEID = TIMEDIM.ID
  LEFT JOIN AOL_SCHEMA.QUERYDIM ON FACTS.QUERYID = QUERYDIM.ID
  LEFT JOIN AOL_SCHEMA.URLDIM ON FACTS.URLID = URLDIM.ID
  WHERE LOWER(QUERYDIM.QUERY) LIKE '%weather%'
    AND (LOWER(URLDIM.URL) LIKE '%weather%'
    OR LOWER(URLDIM.DESRIPTION) LIKE '%weather%')
  AND TIMEDIM.[year] IS NOT NULL
  AND TIMEDIM.[month] IS NOT NULL
  AND TIMEDIM.[day of the month] IS NOT NULL
  ORDER BY YMD_TIMESTAMP ASC
)
SELECT
  DATE_RANGE.EVENT_DATE,
  QUERY_FREQ.[calender week],
  QUERY_FREQ.[day of the week],
  COALESCE(COUNT(QUERY_FREQ.QUERY), 0) AS FREQ
FROM DATE_RANGE
LEFT JOIN QUERY_FREQ
ON DATE_RANGE.EVENT_DATE = QUERY_FREQ.YMD_TIMESTAMP
GROUP BY (DATE_RANGE.EVENT_DATE, QUERY_FREQ.[calender week], QUERY_FREQ.[day of the week])
ORDER BY DATE_RANGE.EVENT_DATE;
```





## Output

Here, we can see the frequency of all weather related queries grouped by date.


	EVENT_DATE	calender week	day of the week	FREQ
0	2006-03-01	9	3	401
1	2006-03-02	9	4	314
2	2006-03-03	9	5	248
3	2006-03-04	9	6	244
4	2006-03-05	9	7	309
...	...	...	...	...
87	2006-05-27	21	6	279
88	2006-05-28	21	7	157
89	2006-05-29	22	1	334
90	2006-05-30	22	2	328
91	2006-05-31	22	3	267

# Question 3

```
WITH TopURLs AS (
    SELECT URLDIM.URL
    FROM AOL_SCHEMA.FACTS
    JOIN AOL_SCHEMA.URLDIM ON AOL_SCHEMA.FACTS.URLID = AOL_SCHEMA.URLDIM.ID
    WHERE AOL_SCHEMA.FACTS.CLICK = 1
    GROUP BY URLDIM.URL
    ORDER BY COUNT(AOL_SCHEMA.FACTS.CLICK) DESC
    LIMIT 20
),
FREQCOMP AS (
    SELECT
        FACTS.ANONID,
        QUERYDIM.QUERY,
        CAST(
            CONCAT(
                '2006-',
                LPAD(CASE
                    WHEN TIMEDIM."day of the year" BETWEEN 60 AND 90 THEN '03'
                    WHEN TIMEDIM."day of the year" BETWEEN 91 AND 120 THEN '04'
                    WHEN TIMEDIM."day of the year" BETWEEN 121 AND 151 THEN '05'
                    ELSE '01'
                END, 2, '0'), '-',
                LPAD(TIMEDIM."day of the month", 2, '0'), '-',
                LPAD(TIMEDIM."hour", 2, '0'), ':',
                LPAD(TIMEDIM."minute", 2, '0'), ':',
                LPAD(TIMEDIM."second", 2, '0')
            ) AS TIMESTAMP
        ) AS time_as_datetime
    FROM
        AOL_SCHEMA.FACTS
    LEFT JOIN AOL_SCHEMA.TIMEDIM ON FACTS.TIMEID = TIMEDIM.ID
    LEFT JOIN AOL_SCHEMA.URLDIM ON FACTS.URLID = URLDIM.ID
    LEFT JOIN AOL_SCHEMA.QUERYDIM ON FACTS.QUERYID = QUERYDIM.ID
```

```
WHERE FACTS.CLICK = 1
    AND (
        URLDIM.URL IN (SELECT URL FROM TopURLs)
        OR LOWER(URLDIM.URL) LIKE '%weather%'
    )
    AND FACTS.ANONID IS NOT NULL
    AND TIMEDIM."hour" IS NOT NULL
    AND TIMEDIM."minute" IS NOT NULL
    AND TIMEDIM."second" IS NOT NULL
    AND TIMEDIM."day of the year" IS NOT NULL
),
DateRange AS (
    SELECT DATE '2006-03-01' AS EVENT_DATE
    UNION ALL SELECT DATE '2006-03-02'
    UNION ALL SELECT DATE '2006-03-03'
    ...
    UNION ALL SELECT DATE '2006-05-31'
)
SELECT
    DateRange.EVENT_DATE AS query_date,
    COALESCE(COUNT(*), 0) AS number_of_queries
FROM
    DateRange
LEFT JOIN
    FREQCOMP E
ON
    CAST(E.time_as_datetime AS DATE) = DateRange.EVENT_DATE
AND LOWER(E.QUERY) LIKE '%tornado%'
GROUP BY
    DateRange.EVENT_DATE
ORDER BY
    query_date;
```

```
WITH DateRange AS (
    SELECT DATE '2006-03-01' AS EVENT_DATE
    UNION ALL SELECT DATE '2006-03-02'
    ...
    UNION ALL SELECT DATE '2006-05-31'
)
SELECT
    DateRange.EVENT_DATE,
    COALESCE(COUNT(E.EPISODE_ID), 0) AS EVENT_COUNT
FROM
    DateRange
LEFT JOIN
    AOL_SCHEMA.WEATHER_EVENTS E
ON
    CAST(E.BEGIN_DATE_TIME AS DATE) = DateRange.EVENT_DATE
    AND E.EVENT_TYPE = 'Tornado'
GROUP BY
    DateRange.EVENT_DATE
ORDER BY
    DateRange.EVENT_DATE;
```



**Working of the query:** These queries count AOL queries and events for each day, utilizing basic aggregate operations and SLICE/DICE.

### Output

	QUERY_DATE	NUMBER_OF_QUERIES
0	2006-03-01	18158
1	2006-03-02	19156
2	2006-03-03	17264
3	2006-03-04	19478
4	2006-03-05	21853
...	...	...
87	2006-05-27	17136
88	2006-05-28	12652
89	2006-05-29	19669
90	2006-05-30	18852
91	2006-05-31	18833

	EVENT_DATE	EVENT_COUNT
0	2006-03-01	318
1	2006-03-02	92
2	2006-03-03	14
3	2006-03-04	35
4	2006-03-05	30
...	...	...
87	2006-05-27	210
88	2006-05-28	191
89	2006-05-29	277
90	2006-05-30	374
91	2006-05-31	280


## Question 4a

```
WITH Events_DATA AS (
    SELECT
        we.EVENT_TYPE,
        we.BEGIN_DATE_TIME,
        we.END_DATE_TIME
    FROM AOL_SCHEMA.WEATHER_EVENTS we
    WHERE we.BEGIN_DATE_TIME >= '2006-03-01 00:01:00.000000'
        AND LOWER(we.EVENT_TYPE) LIKE 'tornado'
),
Relevant_Queries AS (
    SELECT
        QUERIES_WEATHER.QUERY_LOWER_TRIMMED AS QUERY,
        QUERIES_WEATHER.FORMATTED_DATE,
        QUERIES_WEATHER.QUERY_ABOUT,
        we.EVENT_TYPE
    FROM Events_DATA we
    INNER JOIN AOL_SCHEMA.Weather_Reaction_Queries AS QUERIES_WEATHER
        ON QUERIES_WEATHER.FORMATTED_DATE BETWEEN we.BEGIN_DATE_TIME AND we.END_DATE_TIME
),
Grouped_Results AS (
    SELECT
        QUERY,
        QUERY_ABOUT,
        EVENT_TYPE,
        COUNT(*) AS query_count
    FROM Relevant_Queries
    GROUP BY GROUPING SETS (
        (QUERY, QUERY_ABOUT, EVENT_TYPE),
        (QUERY, EVENT_TYPE)
    )
),
```

```

TOKEN_COUNT AS (
    SELECT
        TOKEN,
        COALESCE(QUERY_ABOUT, 'UNKNOWN') AS QUERY_ABOUT, -- Treat NULLs as 'UNKNOWN' for group by
        SUM(query_count) AS token_count
    FROM Tokens_Queries
    GROUP BY TOKEN, QUERY_ABOUT
    HAVING SUM(query_count)>2
    ORDER BY token_count DESC
),
TOTAL_QUERY_COUNT AS (
    SELECT
        QUERY_ABOUT,
        SUM(token_count) AS total_query_count
    FROM TOKEN_COUNT
    GROUP BY QUERY_ABOUT
),
NORMALIZED_TOKEN_COUNT AS (
    SELECT
        tc.TOKEN,
        tc.QUERY_ABOUT,
        tc.token_count,
        tqc.total_query_count,
        CASE
            WHEN tc.QUERY_ABOUT = 'UNKNOWN' THEN
                (tc.token_count * 1.0 /
                 (SELECT SUM(token_count) FROM TOKEN_COUNT WHERE QUERY_ABOUT = 'UNKNOWN'))
            ELSE
                (tc.token_count * 1.0 / tqc.total_query_count)
        END AS Group_Specific-Token_Probability
    FROM TOKEN_COUNT tc
    JOIN TOTAL_QUERY_COUNT tqc
        ON tc.QUERY_ABOUT = tqc.QUERY_ABOUT
)
SELECT
    TOKEN,
    QUERY_ABOUT,
    token_count,
    total_query_count,
    Group_Specific-Token_Probability,
    Group_Specific-Token_Probability*100 AS Group_specific-Token_Percentage
FROM NORMALIZED_TOKEN_COUNT
ORDER BY QUERY_ABOUT,Group_Specific-Token_Probability DESC;
...
```

Key operations utilized: INNER JOIN, GROUPING SETS.



**Working of the query:** This Query obtain the weather queries for each query about (Weather and Tracking Alerts, Damage Assessment and Recovery etc...) during tornado. It also obtains the group specific token probability and percentage.

### Output:


	TOKEN	QUERY_ABOUT	TOKEN_COUNT	TOTAL_QUERY_COUNT	GROUP_SPECIFIC_TOKEN_PROBABILITY	GROUP_SPECIFIC_TOKEN_PERCENTAGE
739	weather	Weather Tracking and Alerts	331	1981	0.167087	16.708733
740	bug	Weather Tracking and Alerts	67	1981	0.033821	3.382130
741	cold	Weather Tracking and Alerts	56	1981	0.028269	2.826855
742	temperature	Weather Tracking and Alerts	46	1981	0.023221	2.322060
743	hurricane	Weather Tracking and Alerts	43	1981	0.021706	2.170621
...	...	...	...	...	...	...
968	cheese	Weather Tracking and Alerts	3	1981	0.001514	0.151439
969	east	Weather Tracking and Alerts	3	1981	0.001514	0.151439
970	changes	Weather Tracking and Alerts	3	1981	0.001514	0.151439
971	handy	Weather Tracking and Alerts	3	1981	0.001514	0.151439
972	knife	Weather Tracking and Alerts	3	1981	0.001514	0.151439

## Question 4b

```
WITH Ordered_Events AS (
    SELECT
        EVENT_TYPE,
        REGION,
        BEGIN_DATE_TIME,
        END_DATE_TIME,
        LEAD(BEGIN_DATE_TIME) OVER (ORDER BY BEGIN_DATE_TIME) AS NEXT_END_DATE_TIME
    FROM AOL_SCHEMA.WEATHER_EVENTS
    WHERE EVENT_TYPE = 'Tornado'
    ORDER BY BEGIN_DATE_TIME
),
Calculated_Events AS (
    SELECT
        EVENT_TYPE,
        BEGIN_DATE_TIME,
        END_DATE_TIME,
        ADD_MINUTES(TO_TIMESTAMP(SUBSTR(END_DATE_TIME, 1, 19)), 1) AS WINDOW_START,
        ADD_MINUTES(TO_TIMESTAMP(SUBSTR(NEXT_END_DATE_TIME, 1, 19)), -1) AS WINDOW_END
    FROM Ordered_Events
),
Window_Events AS (
    SELECT
        EVENT_TYPE,
        BEGIN_DATE_TIME,
        END_DATE_TIME,
        WINDOW_START,
        WINDOW_END
    FROM Calculated_Events
    WHERE SECONDS_BETWEEN(WINDOW_END, WINDOW_START) >= 0
),
Relevant_Queries AS (
    SELECT
        qt.QUERY_LOWER_TRIMMED AS QUERY,
        qt.QUERY_ABOUT,
        qt.FORMATTED_DATE,
        tq.EVENT_TYPE,
        tq.BEGIN_DATE_TIME,
        tq.END_DATE_TIME,
        tq.WINDOW_START,
        tq.WINDOW_END
    FROM Window_Events tq
    INNER JOIN AOL_SCHEMA.Weather_Reaction_Queries qt
    ON qt.FORMATTED_DATE BETWEEN tq.WINDOW_START AND tq.WINDOW_END
),
Grouped_Results AS (
    SELECT
        QUERY,
        EVENT_TYPE,
        QUERY_ABOUT,
        COUNT(*) AS query_count
    FROM Relevant_Queries
    GROUP BY GROUPING SETS (
        (QUERY, EVENT_TYPE, QUERY_ABOUT),
        (QUERY, EVENT_TYPE)
    )
),
```

```
Tokens_Queries AS (
    SELECT
        token.TOKEN,
        ex.EVENT_TYPE,
        ex.QUERY_ABOUT,
        ex.QUERY_COUNT
    FROM Grouped_Results ex
    INNER JOIN AOL_SCHEMA.tokenization_new_queries token
    ON ex.QUERY = token.QUERY
),
TOKEN_COUNT AS (
    SELECT
        TOKEN,
        COALESCE(QUERY_ABOUT, 'UNKNOWN') AS QUERY_ABOUT, -- Treat NULLs as 'UNKNOWN' for group by
        SUM(query_count) AS token_count
    FROM Tokens_Queries
    GROUP BY TOKEN, QUERY_ABOUT
    HAVING SUM(query_count) > 2
    ORDER BY token_count DESC
),
TOTAL_QUERY_COUNT AS (
    SELECT
        QUERY_ABOUT,
        SUM(token_count) AS total_token_count
    FROM TOKEN_COUNT
    GROUP BY QUERY_ABOUT
),
-- Normalize token probabilities for 'UNKNOWN' and other QUERY_ABOUT
NORMALIZED_TOKEN_COUNT AS (
    SELECT
        tc.TOKEN,
        tc.QUERY_ABOUT,
        tc.token_count,
        tqc.total_token_count, -- Correct column name
        CASE
            WHEN tc.QUERY_ABOUT = 'UNKNOWN' THEN
                (tc.token_count * 1.0 /
                 (SELECT SUM(token_count) FROM TOKEN_COUNT WHERE QUERY_ABOUT = 'UNKNOWN'))
            ELSE
                (tc.token_count * 1.0 / tqc.total_token_count) -- Update here as well
        END AS Group_Specific_Token_Probability
    FROM TOKEN_COUNT tc
    JOIN TOTAL_QUERY_COUNT tqc
    ON tc.QUERY_ABOUT = tqc.QUERY_ABOUT
),
-- Final selection with normalized probabilities
SELECT
    TOKEN,
    QUERY_ABOUT,
    token_count,
    total_token_count,
    Group_Specific_Token_Probability,
    Group_Specific_Token_Probability*100 AS Group_Specific_Token_Percentage
FROM NORMALIZED_TOKEN_COUNT
ORDER BY QUERY_ABOUT, Group_Specific_Token_Probability DESC;
```

Key operations utilized: LEAD, ADD\_MINUTES, SECONDS\_BETWEEN, INNER JOIN, GROUPING SETS..



**Working of the query:** This Query obtain the weather queries for each query about (Weather and Tracking Alerts, Damage Assessment and Recovery etc...) after Tornado.. It Also obtain the group specific token probability and percentage.

**Output:**

	TOKEN	QUERY_ABOUT	TOKEN_COUNT	TOTAL_TOKEN_COUNT	GROUP_SPECIFIC_TOKEN_PROBABILITY	GROUP_SPECIFIC_TOKEN_PERCENTAGE
0	insurance	Damage Assessment and Recovery	9625	41534	0.231738	23.173785
1	repair	Damage Assessment and Recovery	3398	41534	0.081812	8.181249
2	health	Damage Assessment and Recovery	1198	41534	0.028844	2.884384
3	auto	Damage Assessment and Recovery	943	41534	0.022704	2.270429
4	life	Damage Assessment and Recovery	852	41534	0.020513	2.051331
...	...	...	...	...	...	...
13971	marco	Weather Tracking and Alerts	3	74301	0.000040	0.004038
13972	cooler	Weather Tracking and Alerts	3	74301	0.000040	0.004038
13973	straw	Weather Tracking and Alerts	3	74301	0.000040	0.004038
13974	brunswick	Weather Tracking and Alerts	3	74301	0.000040	0.004038
13975	killed	Weather Tracking and Alerts	3	74301	0.000040	0.004038



## Code 7:

```
import pandas as pd
import nltk
from nltk.stem import WordNetLemmatizer

# Download required NLTK resources (if you haven't already)
nltk.download('wordnet')
nltk.download('omw-1.4')

# Initialize the lemmatizer
lemmatizer = WordNetLemmatizer()

# Function to lemmatize tokens
def lemmatize_token(token):
    return lemmatizer.lemmatize(token)

# Apply lemmatization to the 'TOKEN' column
query_events['LEMMATIZED_TOKEN'] = query_events['TOKEN'].apply(lemmatize_token)

query_result = query_events.groupby(
    ['QUERY_ABOUT', 'LEMMATIZED_TOKEN'], as_index=False
).agg({
    'GROUP_SPECIFIC_TOKEN_PROBABILITY': 'sum',
    'GROUP_SPECIFIC_TOKEN_PERCENTAGE': 'sum'
})

# Print the result
print(query_result)
```

This code performs word lemmatization, converting words to their base form, and appends their associated group-specific token probability and percentage.

Libraries used: nltk

Required nltk resources: wordnet, omw-1.4





## Code 8:

```
during_tokens = query_during_tornado[['LEMMAIZED_TOKEN', 'GROUP_SPECIFIC_TOKEN_PROBABILITY']]
after_tokens = query_after_tornado[['LEMMAIZED_TOKEN', 'GROUP_SPECIFIC_TOKEN_PROBABILITY']]

# Create weighted frequency dictionaries for both during and after tornado
def create_weighted_dict(tokens_df):
    """
    Creates a dictionary of tokens with their respective probability values.
    """
    return dict(zip(tokens_df['LEMMAIZED_TOKEN'], tokens_df['GROUP_SPECIFIC_TOKEN_PROBABILITY']))

# Create the weighted dictionaries for both during and after tornado groups
during_weighted_dict = create_weighted_dict(during_tokens)
after_weighted_dict = create_weighted_dict(after_tokens)

# Find common tokens between the two dataframes
common_tokens = set(during_weighted_dict.keys()) & set(after_weighted_dict.keys())

## Filter the weighted dictionaries to include only common tokens
common_during_dict = {token: during_weighted_dict[token] for token in common_tokens}
common_after_dict = {token: after_weighted_dict[token] for token in common_tokens}

unique_during_tokens = set(during_weighted_dict.keys()) - set(after_weighted_dict.keys())
unique_after_tokens = set(after_weighted_dict.keys()) - set(during_weighted_dict.keys())

# Filter the weighted dictionaries to include only common tokens
unique_during_dict = {token: during_weighted_dict[token] for token in unique_during_tokens}
unique_after_dict = {token: after_weighted_dict[token] for token in unique_after_tokens}

# Word Cloud for During Tornado
unique_during_wordcloud = WordCloud(width=800, height=400, background_color='white').generate_from_frequencies(unique_during_dict)

# Word Cloud for After Tornado
unique_after_wordcloud = WordCloud(width=800, height=400, background_color='white').generate_from_frequencies(unique_after_dict)
```

This code filters the common and distinct words between during and after tornado.

## Query 5a

```
SELECT
  T1.ANONID,
  T1.TIME_AS_DATETIME,
  COALESCE(LAG(TIME_AS_DATETIME) OVER (PARTITION BY ANONID ORDER BY TIME_AS_DATETIME), TIME_AS_DATETIME) AS LaggedDateTime,
  SECONDS_BETWEEN(T1.TIME_AS_DATETIME, COALESCE(LAG(TIME_AS_DATETIME) OVER (PARTITION BY ANONID ORDER BY TIME_AS_DATETIME), TIME_AS_DATETIME)) as Seconds_Difference,
  MINUTES_BETWEEN(T1.TIME_AS_DATETIME, COALESCE(LAG(TIME_AS_DATETIME) OVER (PARTITION BY ANONID ORDER BY TIME_AS_DATETIME), TIME_AS_DATETIME)) as Minutes_Difference
FROM
  AOL_SCHEMA.INTERARRIVAL_TIMES as T1
WHERE
  T1.ANONID IN (
    SELECT T2.ANONID
    FROM AOL_SCHEMA.INTERARRIVAL_TIMES as T2
    GROUP BY T2.ANONID
    HAVING COUNT(T2.ANONID) >= 10
  )
  AND NOT EXISTS(
    SELECT 1
    FROM AOL_SCHEMA.WEATHER_EVENTS as T3
    WHERE
      (T1.TIME_AS_DATETIME BETWEEN T3.BEGIN_DATE_TIME AND T3.END_DATE_TIME)
      AND (T3.EVENT_TYPE = 'Tornado')
  )
ORDER BY
  T1.ANONID,
  T1.TIME_AS_DATETIME
```

**Key operations utilized:** Coalesce, Partition By ,Seconds/Minutes Between, Slice/Dice



### Working of the query:

Retrieves the UserID, time, lagged time, and interclick times (in seconds and minutes) for users who clicked on at least 10 of the top 20 most popular links, excluding clicks during disasters.

### Output

	ANONID	TIME_AS_DATETIME	LAGGEDDATETIME	SECONDS_DIFFERENCE	MINUTES_DIFFERENCE
0	15	2006-03-11 09:55:17.000000	2006-03-11 09:55:17.000000	0	0.000000
1	15	2006-03-18 21:02:45.000000	2006-03-11 09:55:17.000000	644848	10747.466667
2	15	2006-03-18 21:06:01.000000	2006-03-18 21:02:45.000000	196	3.266667
3	15	2006-03-21 19:55:51.000000	2006-03-18 21:06:01.000000	254990	4249.833333
4	15	2006-03-21 20:09:22.000000	2006-03-21 19:55:51.000000	811	13.516667
...	...	...	...	...	...
999853	657399	2006-04-11 09:28:37.000000	2006-04-11 09:22:01.000000	396	6.600000
999854	657399	2006-04-11 09:33:27.000000	2006-04-11 09:28:37.000000	290	4.833333
999855	657399	2006-04-11 09:36:22.000000	2006-04-11 09:33:27.000000	175	2.916667
999856	657399	2006-04-24 19:48:08.000000	2006-04-11 09:36:22.000000	1159906	19331.766667
999857	657399	2006-04-29 19:11:47.000000	2006-04-24 19:48:08.000000	429819	7163.650000



## Query 5b

```
SELECT
  T1.ANONID,
  T1.TIME_AS_DATETIME,
  COALESCE(LAG(TIME_AS_DATETIME) OVER (PARTITION BY ANONID ORDER BY TIME_AS_DATETIME), TIME_AS_DATETIME) AS LaggedDateTime,
  SECONDS_BETWEEN(T1.TIME_AS_DATETIME, COALESCE(LAG(TIME_AS_DATETIME) OVER (PARTITION BY ANONID ORDER BY TIME_AS_DATETIME), TIME_AS_DATETIME)) as Seconds_Difference,
  MINUTES_BETWEEN(T1.TIME_AS_DATETIME, COALESCE(LAG(TIME_AS_DATETIME) OVER (PARTITION BY ANONID ORDER BY TIME_AS_DATETIME), TIME_AS_DATETIME)) as Minutes_Difference
FROM
  AOL_SCHEMA.INTERARRIVAL_TIMES as T1
WHERE
  T1.ANONID IN (
    SELECT T2.ANONID
    FROM AOL_SCHEMA.INTERARRIVAL_TIMES as T2
    GROUP BY T2.ANONID
    HAVING COUNT(T2.ANONID) >= 10
  )
  AND EXISTS(
    SELECT 1
    FROM AOL_SCHEMA.WEATHER_EVENTS as T3
    WHERE
      (T1.TIME_AS_DATETIME BETWEEN T3.BEGIN_DATE_TIME AND T3.END_DATE_TIME)
      AND (T3.EVENT_TYPE = 'Tornado')
  )
ORDER BY
  T1.ANONID,
  T1.TIME_AS_DATETIME
```

**Key operations utilized:** Coalesce, Partition By, Seconds/Minutes Difference, Exists



**Working of the query:** Retrieves the UserID, time, lagged time, and interclick times (in seconds and minutes) for users who clicked on at least 10 of the top 20 most popular links during a tornado

## Output

	ANONID	TIME_AS_DATETIME	LAGGEDDATETIME	SECONDS_DIFFERENCE	MINUTES_DIFFERENCE
0	25	2006-04-02 20:15:56.000000	2006-04-02 20:15:56.000000	0	0.000000
1	25	2006-04-15 15:55:54.000000	2006-04-02 20:15:56.000000	1107598	18459.966667
2	25	2006-04-15 17:30:44.000000	2006-04-15 15:55:54.000000	5690	94.833333
3	29	2006-03-12 19:47:08.000000	2006-03-12 19:47:08.000000	0	0.000000
4	29	2006-03-12 21:54:36.000000	2006-03-12 19:47:08.000000	7648	127.466667
...	...	...	...	...	...
28512	657282	2006-04-16 13:35:13.000000	2006-04-16 13:35:13.000000	0	0.000000
28513	657283	2006-04-02 16:37:24.000000	2006-04-02 16:37:24.000000	0	0.000000
28514	657283	2006-04-02 19:10:12.000000	2006-04-02 16:37:24.000000	9168	152.800000
28515	657283	2006-04-02 19:10:12.000000	2006-04-02 19:10:12.000000	0	0.000000
28516	657307	2006-04-07 15:49:40.000000	2006-04-07 15:49:40.000000	0	0.000000

# Bonus Question - a

This query identifies the most clicked domains or URLs and matches them by time to specific weather events and regions where they occurred, ranking them based on the number of clicks

```
1 WITH ClickedDomains AS (  
2     SELECT  
3         AOL_SCHEMA.WEATHER_EVENTS.REGION AS REGION,  
4         AOL_SCHEMA.WEATHER_EVENTS.EVENT_TYPE AS EVENT_TYPE,  
5         AOL_SCHEMA.WEATHER_EVENTS.BEGIN_DATE_TIME AS BEGIN_DATE_TIME,  
6         AOL_SCHEMA.URLDIM.THISDOMAIN AS THISDOMAIN,  
7         AOL_SCHEMA.URLDIM.URL AS URL,  
8         COUNT(AOL_SCHEMA.FACTS.URLID) AS CLICK_COUNT  
9     FROM  
10        AOL_SCHEMA.WEATHER_EVENTS  
11    JOIN  
12        AOL_SCHEMA.FACTS  
13    ON AOL_SCHEMA.WEATHER_EVENTS.BEGIN_DAY = AOL_SCHEMA.FACTS.TIMEID  
14    JOIN  
15        AOL_SCHEMA.URLDIM  
16    ON AOL_SCHEMA.FACTS.URLID = AOL_SCHEMA.URLDIM.ID  
17 WHERE  
18     AOL_SCHEMA.FACTS.CLICK = TRUE  
19     AND (AOL_SCHEMA.URLDIM.THISDOMAIN IS NOT NULL OR AOL_SCHEMA.URLDIM.URL IS NOT NULL)  
20     AND AOL_SCHEMA.WEATHER_EVENTS.BEGIN_DATE_TIME BETWEEN '2006-03-01 00:00:00' AND '2006-05-31 23:59:59'  
21 GROUP BY ROLLUP(  
22     AOL_SCHEMA.WEATHER_EVENTS.REGION,  
23     AOL_SCHEMA.WEATHER_EVENTS.EVENT_TYPE,  
24     AOL_SCHEMA.WEATHER_EVENTS.BEGIN_DATE_TIME,  
25     AOL_SCHEMA.URLDIM.THISDOMAIN,  
26     AOL_SCHEMA.URLDIM.URL  
27 )  
28 ),
```

```
29 RankedDomains AS (  
30     SELECT  
31         REGION,  
32         EVENT_TYPE,  
33         BEGIN_DATE_TIME,  
34         THISDOMAIN,  
35         URL,  
36         CLICK_COUNT,  
37         ROW_NUMBER() OVER (  
38             PARTITION BY REGION, EVENT_TYPE  
39             ORDER BY CLICK_COUNT DESC  
40         ) AS RANK  
41     FROM  
42        ClickedDomains  
43     WHERE  
44        THISDOMAIN IS NOT NULL OR URL IS NOT NULL  
45 )  
46 SELECT  
47     REGION,  
48     EVENT_TYPE,  
49     BEGIN_DATE_TIME,  
50     THISDOMAIN,  
51     URL,  
52     CLICK_COUNT  
53 FROM  
54     RankedDomains  
55 WHERE  
56     RANK = 1  
57 ORDER BY  
58     REGION,  
59     EVENT_TYPE,  
60     BEGIN_DATE_TIME;
```

# Output

	REGION	EVENT_TYPE	BEGIN_DATE_TIME	THISDOMAIN	URL	CLICK_COUNT
0	Alabama	Flash Flood	2006-03-20 18:45:00.000000	nau	http://www.nau.edu	3
1	Alabama	Funnel Cloud	2006-03-20 17:55:00.000000	nau	http://www.nau.edu	3
2	Alabama	Hail	2006-04-20 17:08:00.000000	nau	http://www.nau.edu	6
3	Alabama	Lightning	2006-04-18 18:10:00.000000	citysearch	http://pittsburgh.citysearch.com	1
4	Alabama	Strong Wind	2006-03-09 14:15:00.000000	ca	http://gocalif.ca.gov	1
...	...	...	...	...	...	...
487	Wyoming	Heavy Snow	2006-05-09 04:00:00.000000	ca	http://gocalif.ca.gov	2
488	Wyoming	Lightning	2006-05-08 14:10:00.000000	ebay.co	http://www.ebay.co.uk	1
489	Wyoming	Thunderstorm Wind	2006-05-26 16:39:00.000000	yahoo	http://mail.yahoo.com	1
490	Wyoming	Wildfire	2006-04-10 09:00:00.000000	bilkent.edu	http://web.bilkent.edu.tr	1
491	Wyoming	Winter Storm	2006-04-24 01:00:00.000000	sharesong	http://www.sharesong.org	4
492 rows × 6 columns						

# Bonus Question - b

This query returns the top 10 most clicked URLs / domains, that correspond to the certain weather events by time

```
1 WITH ClickedDomains AS (  
2     SELECT  
3         AOL_SCHEMA.WEATHER_EVENTS.REGION AS REGION,  
4         AOL_SCHEMA.WEATHER_EVENTS.EVENT_TYPE AS EVENT_TYPE,  
5         AOL_SCHEMA.WEATHER_EVENTS.BEGIN_DATE_TIME AS BEGIN_DATE_TIME,  
6         AOL_SCHEMA.URLDIM.THISDOMAIN AS THISDOMAIN,  
7         AOL_SCHEMA.URLDIM.URL AS URL,  
8         COUNT(AOL_SCHEMA.FACTS.URLID) AS CLICK_COUNT  
9     FROM  
10        AOL_SCHEMA.WEATHER_EVENTS  
11     JOIN  
12        AOL_SCHEMA.FACTS  
13        ON AOL_SCHEMA.WEATHER_EVENTS.BEGIN_DAY = AOL_SCHEMA.FACTS.TIMEID  
14     JOIN  
15        AOL_SCHEMA.URLDIM  
16        ON AOL_SCHEMA.FACTS.URLID = AOL_SCHEMA.URLDIM.ID  
17     WHERE  
18        AOL_SCHEMA.FACTS.CLICK = TRUE  
19        AND (AOL_SCHEMA.URLDIM.THISDOMAIN IS NOT NULL OR AOL_SCHEMA.URLDIM.URL IS NOT NULL)  
20        AND AOL_SCHEMA.WEATHER_EVENTS.BEGIN_DATE_TIME BETWEEN '2006-03-01 00:00:00' AND '2006-05-31 23:59:59'  
21     GROUP BY  
22        AOL_SCHEMA.WEATHER_EVENTS.REGION,  
23        AOL_SCHEMA.WEATHER_EVENTS.EVENT_TYPE,  
24        AOL_SCHEMA.WEATHER_EVENTS.BEGIN_DATE_TIME,  
25        AOL_SCHEMA.URLDIM.THISDOMAIN,  
26        AOL_SCHEMA.URLDIM.URL  
27 ),  
28 RankedDomains AS (  
29     SELECT  
30         REGION,  
31         EVENT_TYPE,  
32         BEGIN_DATE_TIME,  
33         THISDOMAIN,  
34         URL,  
35         CLICK_COUNT,  
36         ROW_NUMBER() OVER (  
37             PARTITION BY REGION  
38             ORDER BY CLICK_COUNT DESC, BEGIN_DATE_TIME ASC  
39         ) AS RANK  
40     FROM  
41        ClickedDomains  
42 )  
43 SELECT  
44     REGION,  
45     EVENT_TYPE,  
46     BEGIN_DATE_TIME,  
47     THISDOMAIN,  
48     URL,  
49     CLICK_COUNT  
50 FROM  
51     RankedDomains  
52 WHERE  
53     RANK = 1  
54 ORDER BY CLICK_COUNT DESC  
55 LIMIT 10;
```





# Output

	REGION	EVENT_TYPE	BEGIN_DATE_TIME	THISDOMAIN	URL	CLICK_COUNT
0	Mississippi	Flash Flood	2006-03-20 15:00:00.000000	nau	http://www.nau.edu	12
1	Oklahoma	Wildfire	2006-03-15 12:00:00.000000	yahoo	http://mail.yahoo.com	10
2	North dakota	Flood	2006-04-01 00:00:00.000000	lib.rochester	http://www.lib.rochester.edu	9
3	South carolina	Hail	2006-05-20 13:50:00.000000	nau	http://www.nau.edu	9
4	Minnesota	Flood	2006-04-01 00:00:00.000000	nintendo	http://www.nintendo.com	8
5	Missouri	Hail	2006-04-02 14:30:00.000000	the-antiaging-site	http://www.the-antiaging-site.com	8
6	Indiana	Flash Flood	2006-03-12 05:30:00.000000	ikea	http://www.ikea.com	7
7	Texas	High Wind	2006-03-20 12:05:00.000000	nau	http://www.nau.edu	6
8	Washington	Thunderstorm Wind	2006-04-15 15:15:00.000000	yahoo	http://mail.yahoo.com	6
9	North carolina	Winter Weather	2006-03-20 12:00:00.000000	nau	http://www.nau.edu	6

# Bonus Question diagram creation code

The output is on the slide 61

```
import matplotlib.pyplot as plt
import matplotlib.cm as cm
import numpy as np

# Generate a list of unique colors for each region
regions = top_domains['REGION'].unique()
colors = cm.tab20(np.linspace(0, 1, len(regions))) # Use colormap to generate colors
region_color_map = {region: colors[i] for i, region in enumerate(regions)} # Map each region to a unique color

# Add a small reduced offset to CLICK_COUNT for overlapping points
jittered_clicks = top_domains.copy()
jittered_clicks['JITTERED_CLICK_COUNT'] = jittered_clicks['CLICK_COUNT']
jittered_clicks.loc[jittered_clicks.duplicated(subset=['EVENT_TYPE', 'CLICK_COUNT'], keep=False), 'JITTERED_CLICK_COUNT'] += np.linspace(-0.1, 0.1, sum(jittered_clicks.duplicated(subset=['EVENT_TYPE', 'CLICK_COUNT'], keep=False)))

# Create the scatter plot
plt.figure(figsize=(16, 10))
for i, row in jittered_clicks.iterrows():
    plt.scatter(row['EVENT_TYPE'], row['JITTERED_CLICK_COUNT'], color=region_color_map[row['REGION']], s=150, alpha=0.7)

# Create the legend
legend_elements = [
    plt.Line2D([0], [0], marker='o', color='w', markerfacecolor=region_color_map[region],
               markersize=10, label=f'{region} \n (row\'URL\'[:30]){\'...\'} if len(row[\'URL\']) > 30 else \'')
    for region, row in jittered_clicks.groupby('REGION').first().iterrows()
]
plt.legend(handles=legend_elements, title="Region (URL)", bbox_to_anchor=(1.05, 1), loc='upper left', fontsize=10)

# Add titles and labels
plt.title('Clicks by Event Type and Region', fontsize=16)
plt.xlabel('Event Type', fontsize=14)
plt.ylabel('Click Count', fontsize=14)
plt.xticks(rotation=30, ha='right', fontsize=12) # Rotate x-axis labels for readability
plt.grid(axis='y', linestyle='--', alpha=0.7) # Add a light grid for clarity
plt.tight_layout()

# Show the plot
plt.show()
```



## References

- <https://www.ncei.noaa.gov/pub/data/swdi/stormevents/csvfiles/legacy/>
- <https://www.ncdc.noaa.gov/stormevents/ftp.jsp>
- A Picture of Search
- GitHub: [https://github.com/chandlerNick/BHT\\_BI\\_WiSe2425.git](https://github.com/chandlerNick/BHT_BI_WiSe2425.git)



## Bonus Slide - How to deal with the old DB

Tips on getting the DB running (in the event our presentation is posted to moodle):

1. Install virtual box
2. Load your database image
3. Ensure you use both the NAT and Host only adapter in network settings
4. Install ODBC Data Sources and test a system DSN with the proper credentials
5. Use the given fingerprint in between the ip address and port
6. If using pyexasol, ensure you use the fingerprint again and that the protocol is the oldest one.

I hope this helps.



# Problem Requirements

## Subtasks

1. **Define five interesting analysis question on this data set.** You might pick up more, since not all chosen questions are answerable with the existing data and your additional data sources.
2. **Import missing data from one additional data source of your choice** for resolving your queries into the database. Use your knowledge on JDBC and Extract-Transform-Load. Please check legal issues when importing data from “The Web”.
3. **Formalize at least five of your queries with ROLAP Statements on EXASOL.** Utilize operators such as SLICE, DICE, CUBE, ROLLUP, PARTITION BY, GROUPING SETS and other standard SQL statements such as joins, unions or intersections etc. (see the EXASOL manual for details on the syntax). You might also use PANDAS or Python functions to predict from the data.
4. **Display your results as charts**, for example with <http://d3js.org> or JFreeChart
5. **Create a presentation for about 15 minutes** and explain your analysis goal, your data sets, showcase selected “cool/surprising” queries and results/insights, explain why this is an important valuable finding, show your schema and explain your workload.
6. **Create an appendix in your presentation**, where you **show the ROLAP queries and results** as screenshots. Name on each slide, what this query should have done. Add to the appendix screenshots of the tables you created, including schema information.
7. **Upload this presentation to the Moodle-system** with a filename <your name> (PDF/PPT) and present it in front of your peers. Check if your peers liked it and considered it insightful. ☺