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Verisk Analytics

# Fueling Innovation From Raw Data

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**ISO Innovative Analytics**

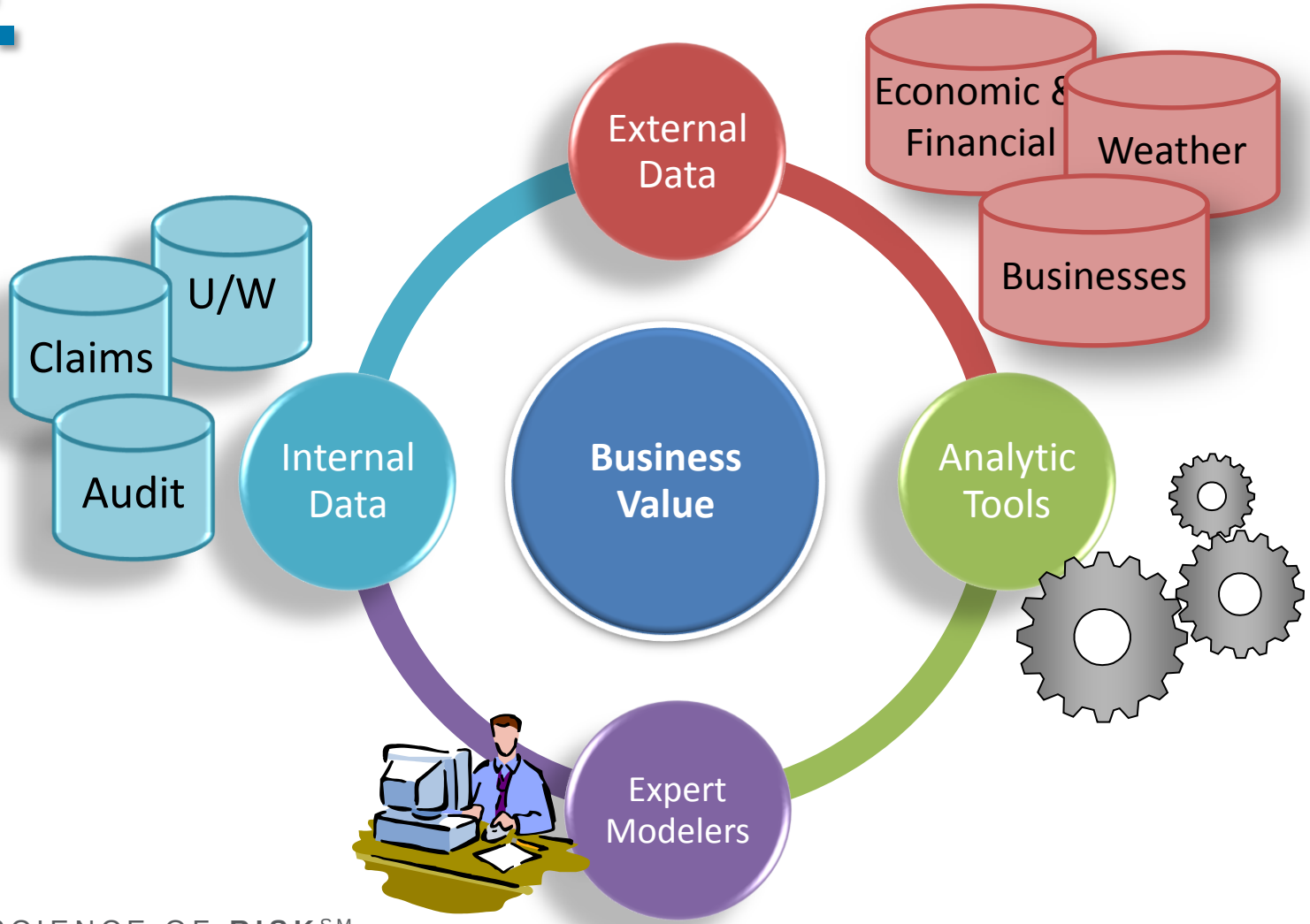
**March 2012**

THE SCIENCE OF **RISK**SM

# Agenda

- **Data**
  - Value, opportunities, and challenges
- **Speed to market?**
  - *Analytic objects* (components) to the rescue
- **Examples of Raw Data**
  - Business locations data in personal auto
  - Weather data in homeowners peril-level modeling
  - Economic growth data in premium audit modeling

# Driving Business Value with Analytics



# Data: Opportunities and Challenges

## Opportunities

- Increasing diversity and volume of useful data
  - Free and fee-based
- Ability to store large data sets
  - Decreasing costs of storage
- Computing capabilities to manipulate large data sets
  - Ever-increasing compute power

## Challenges

- Complex data structures
- Sheer volume
- Multitude of variables
  - Significant preprocessing
- Data management
  - Storage and refresh
- Raw data is rarely useful
  - Need right techniques and tools to extract value

**Considerable value but speed to market remains a concern**

# Business Locations Data

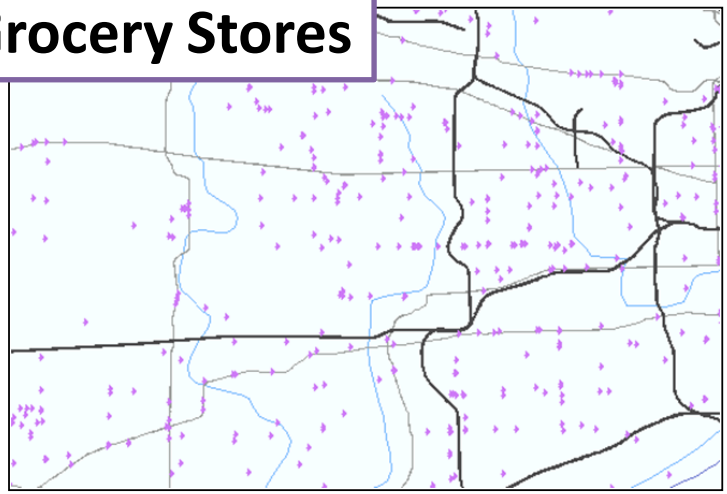
# Problem – Geographic Risk Estimation

# The Data: Business Points

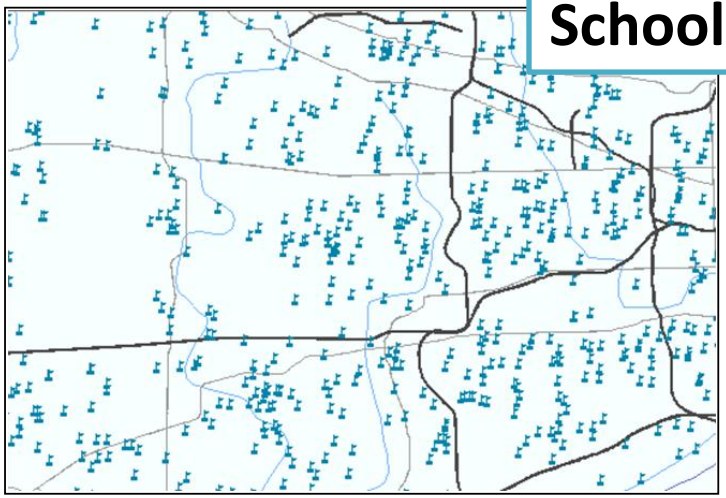
- From a business data vendor (fee-based)
  - 13 million businesses
  - Latitude/longitude
  - 108 distinct SIC codes
- Identify "traffic generators"
  - Businesses that produce traffic in their vicinity
    - e.g., malls/shopping centers, transportation hubs, etc.

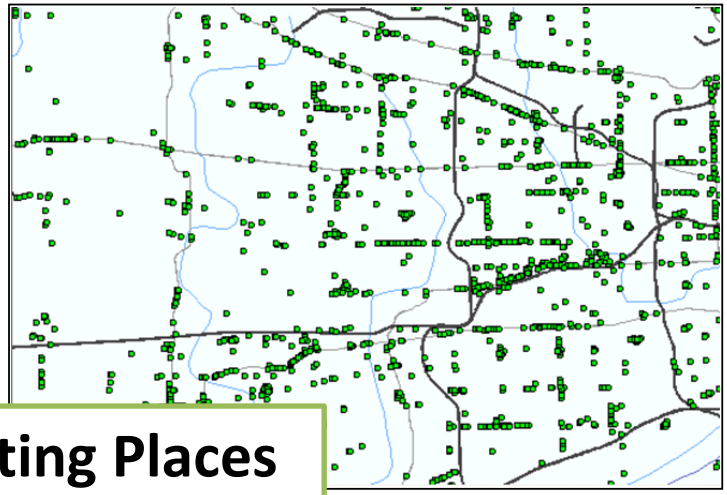
# Examples of Traffic Generators

Grocery Stores

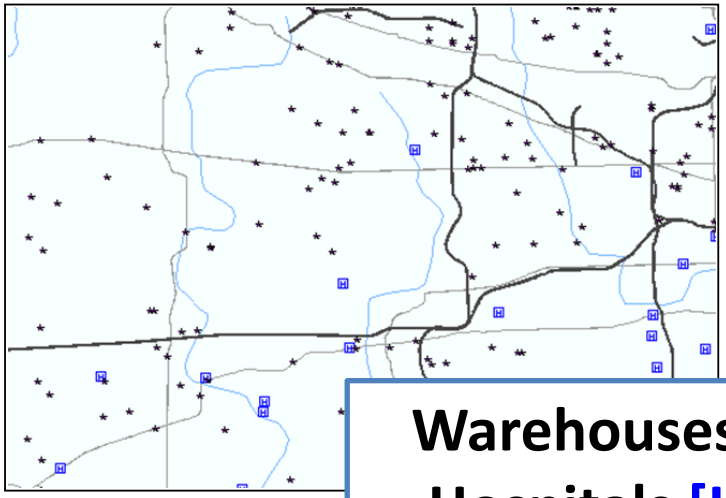


Schools



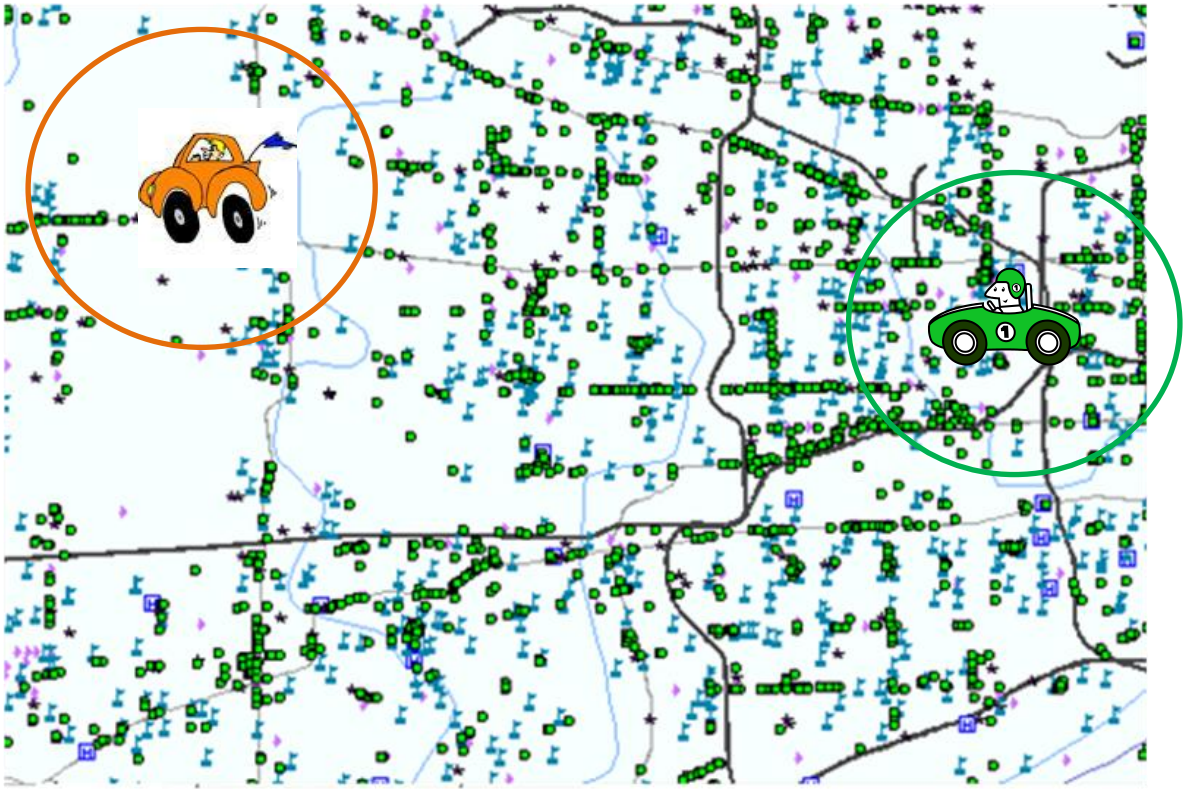


Eating Places



Warehouses *
Hospitals [H]

# Traffic Generators and Auto Losses



- **Distribution of businesses (traffic generators) are different at these two garaging locations**
- **Is there a correlation between these traffic generators and auto losses?**

# Deriving Useful Features

| Count of Grocery Stores within .50 miles | Count of Grocery Stores within 5 miles | Count of Hospitals within .50 miles | Count of Hospitals within 5 miles | Count of Eating Places within .50 miles | Count of Eating Places within 5 miles |
|---|---|---|---|---|---|
| 1 | 48 | 0 | 1 | 9 | 240 |
| 0 | 174 | 0 | 9 | 10 | 970 |

- **Numerous "calculated" dimensions**
  - Distance to nearest business of a certain type
  - Number of businesses of a type within a radius "R"
    - R = 0.25, 0.5, 1, 2, 5, 10, etc.
  - Density estimates
    - Per capita variables, etc.



Area coverage – ½ mile radius = < 1 square mile; 5 mile radius ~ 80 square miles

# Traffic Generators Are Correlated

Correlations among Traffic Generators at ½ Mile

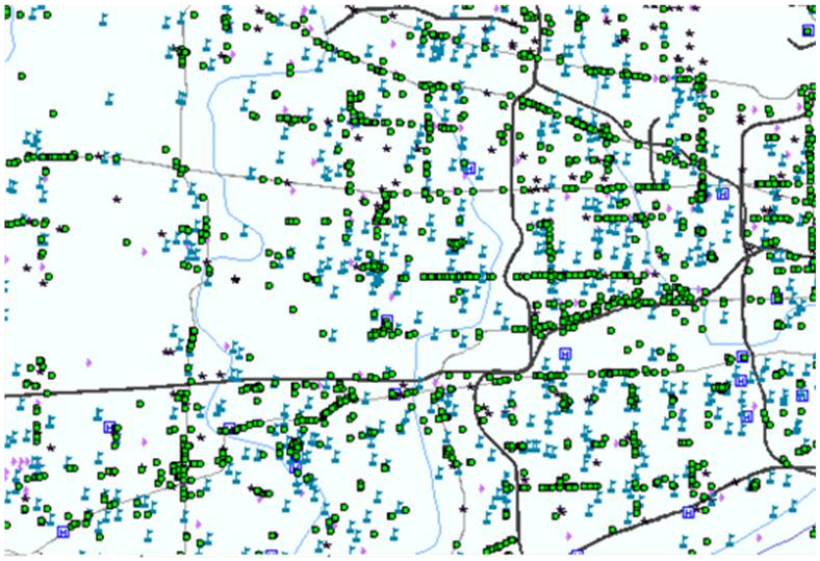
| | Grocery 1/2 Mile |
|---|---|
| Grocery 1/2 Mile | 1 |
| School 1/2 Mile | 0.658 |
| Warehouse 1/2 Mile | 0.564 |
| Hospital 1/2 Mile | 0.338 |
| Eating Places 1/2 Mile | 0.814 |

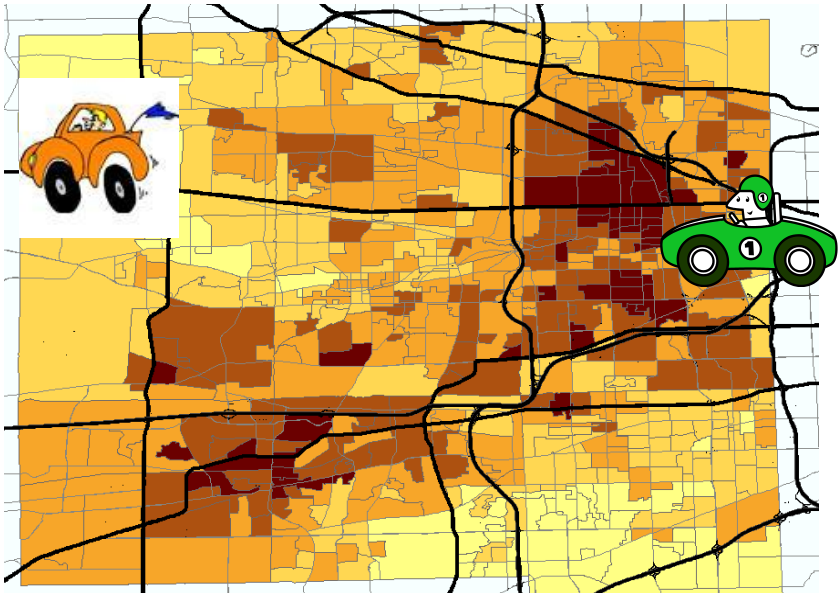
Correlations among Traffic Generators at 5 Miles

| | Grocery 5 Miles | School 5 Miles | Warehouse 5 Miles | Hospital 5 Miles | Eating Places 5 Miles |
|---|---|---|---|---|---|
| Grocery 5 Miles | 1 | | | | |
| School 5 Miles | 0.969 | 1 | | | |
| Warehouse 5 Miles | 0.958 | 0.960 | 1 | | |
| Hospital 5 Miles | 0.871 | 0.859 | 0.879 | 1 | |
| Eating Places 5 Miles | 0.984 | 0.954 | 0.967 | 0.913 | 1 |

- At ½ mile the traffic generators are moderately correlated
- At 5 miles the traffic generators are very highly correlated
- Selecting from highly correlated variables is problematic

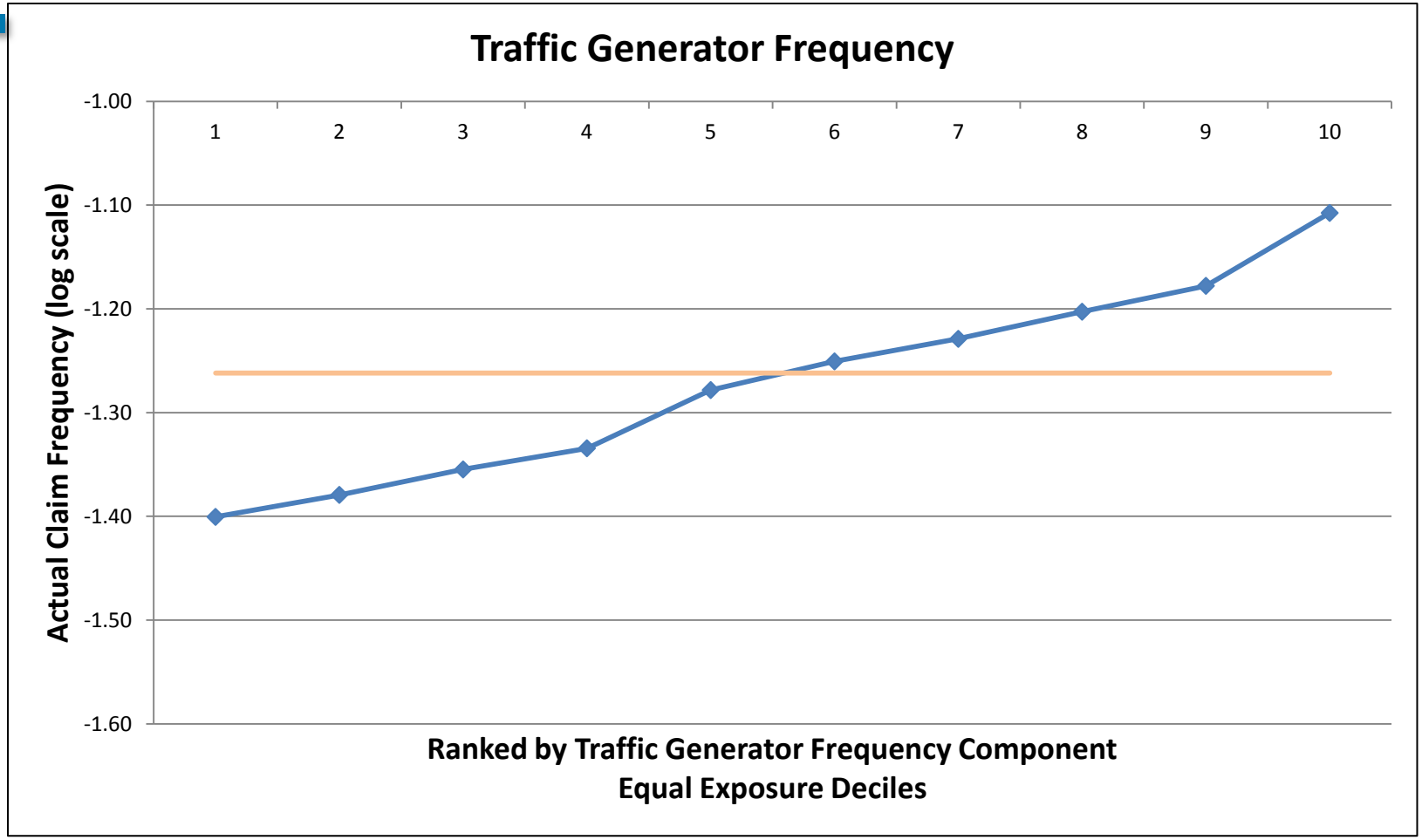
# Collision Frequency Model





- Collision frequency as a function of traffic generators — darker shades represent higher collision frequencies
- This model uses a complex set of traffic generators at various distances

# Components as Predictors



# Personal Auto Environment Model:
## Components and Examples

- **Weather/Terrain**:
  - Measures of snowfall
  - Measures of rainfall
  - Measures of temperature
  - Elevation changes
- **Traffic Density and Driving Patterns**:
  - Commute patterns
  - Public transportation usage
  - Daytime occupancy
  - Speed limits
  - Traffic loads
- **Traffic Composition**:
  - Demographic groups e.g.
    - Household size, home ownership
  - Age distribution
  - Housing occupancy
- **Traffic Generators**:
  - Transportation hubs
  - Shopping centers
  - Hospitals/medical centers
  - Entertainment districts
- **Experience and Trend**:
  - ISO loss cost
  - State frequency/severity trends

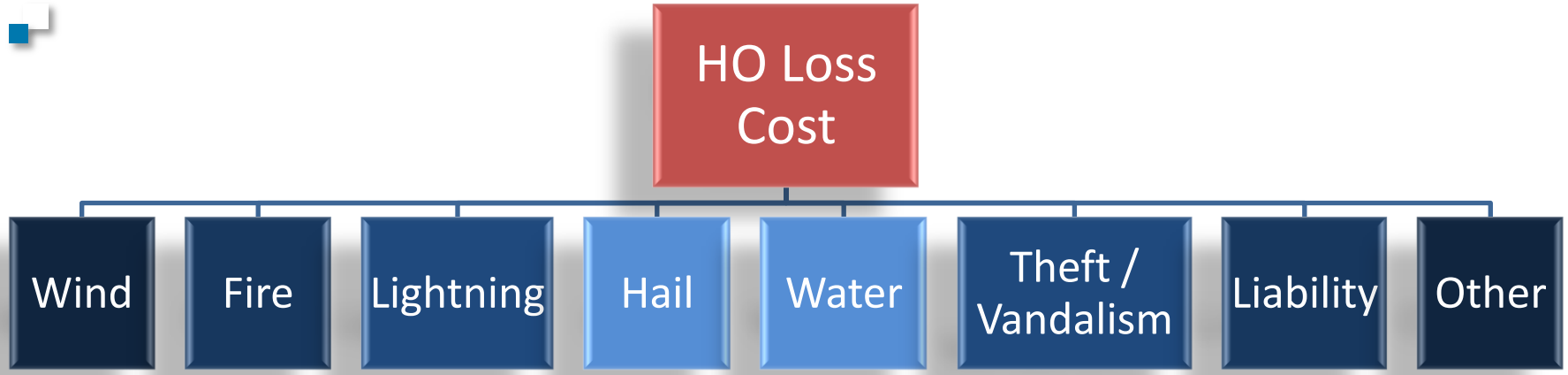
# Increased Segmentation and Value

| Model | Gini Index | Value of Lift |
|---|---|---|
| Current Territories | 8.37% | - |
| Environmental Module -Base Industry Model | 9.49% | $2.75 |
| Insurer Custom Model Using Components | 10.31% | $6.98 |

- Modeling using components doubled incremental lift over current territories

# Weather Data

# Homeowners Peril-Level Risk Estimation



# The Data: NARR Weather Data

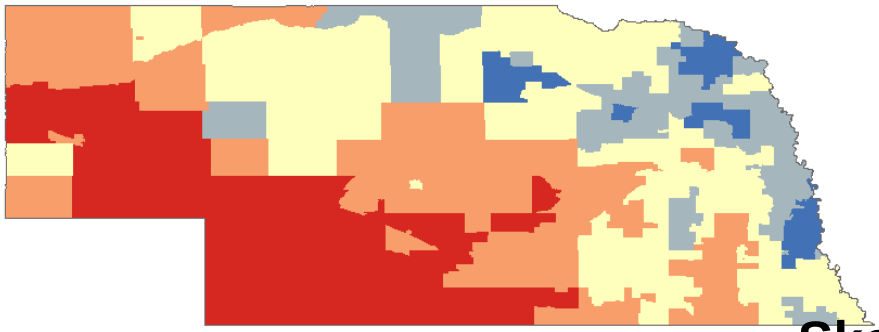
- North American Regional Reanalysis (NARR)
  - "Best/most accurate North American weather and climate data set"
- Data Range – 1979–2007
- Granularity – 32 x 32 km grid
- 8 daily readings (every 3 hours) – raw data
  - Accumulated precipitation
  - Air temperature
  - Rain
  - Wind
  - Relative humidity
  - Snow depth
  - etc.
- Data size ~ 150 GB

# Derive Potentially Useful Features

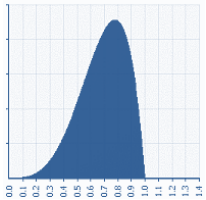
- Temperature
  - Mean
  - Maximum deviation from mean
  - Daily range = Daily max – Daily min
  - Number of consecutive days below freezing, etc.
- Wind
  - Number of days with high wind, etc.
- Precipitation
  - Number of days with severe precipitation
  - Number of days without precipitation, etc.
- Interactions
  - Days without precipitation, high temperature, and high wind, etc.

# Explore Higher-Order Moments

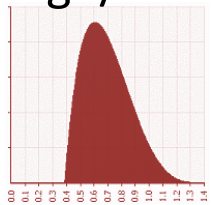
**Mean of Temperature Range**



Low/Neg



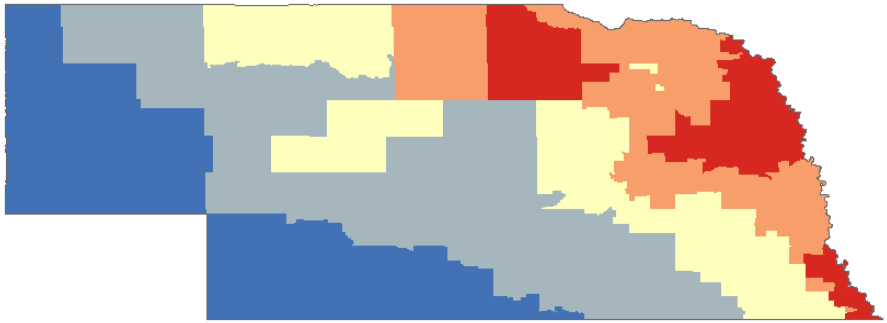
High/Pos



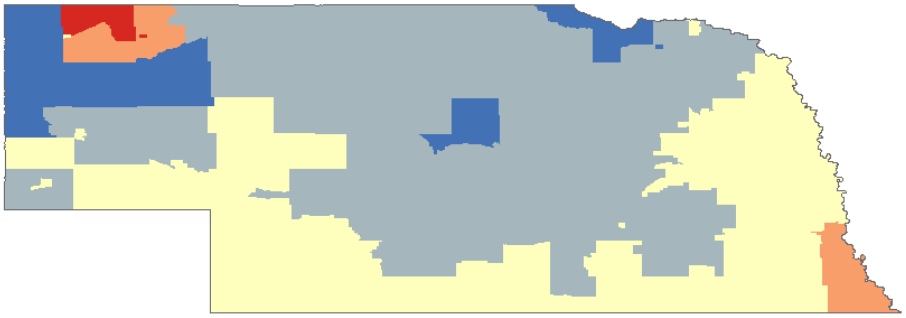
Range = Max – Min

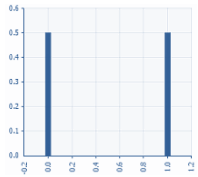
Low  High

**Skewness of Temperature Range**

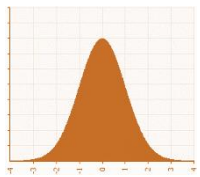


**Kurtosis of Temperature Range**

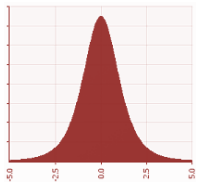




Low/1



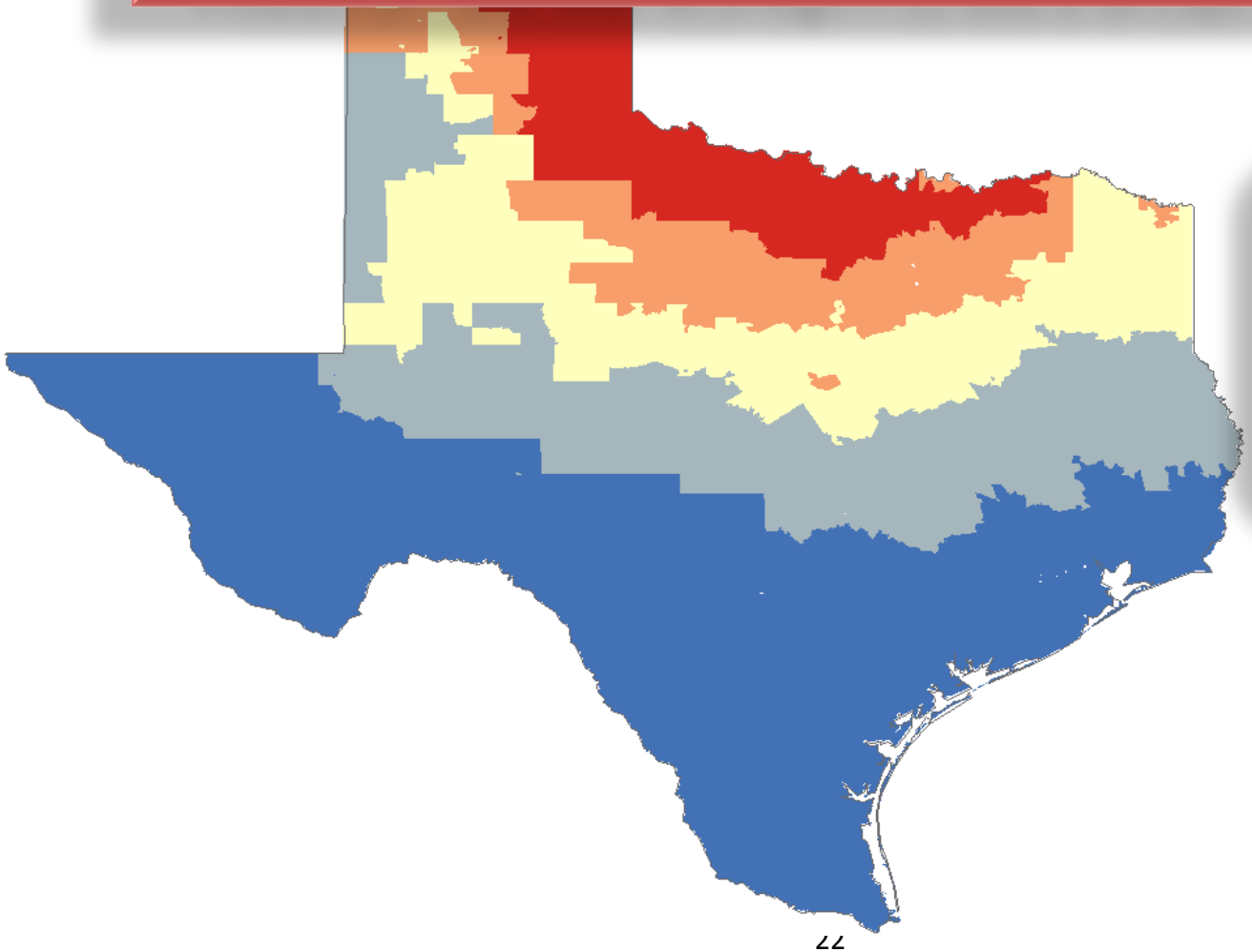
Med/3



High/∞

# Explore Interactions: Use Visualization

Product of - % of days with high < 32 and % of days with low > 72

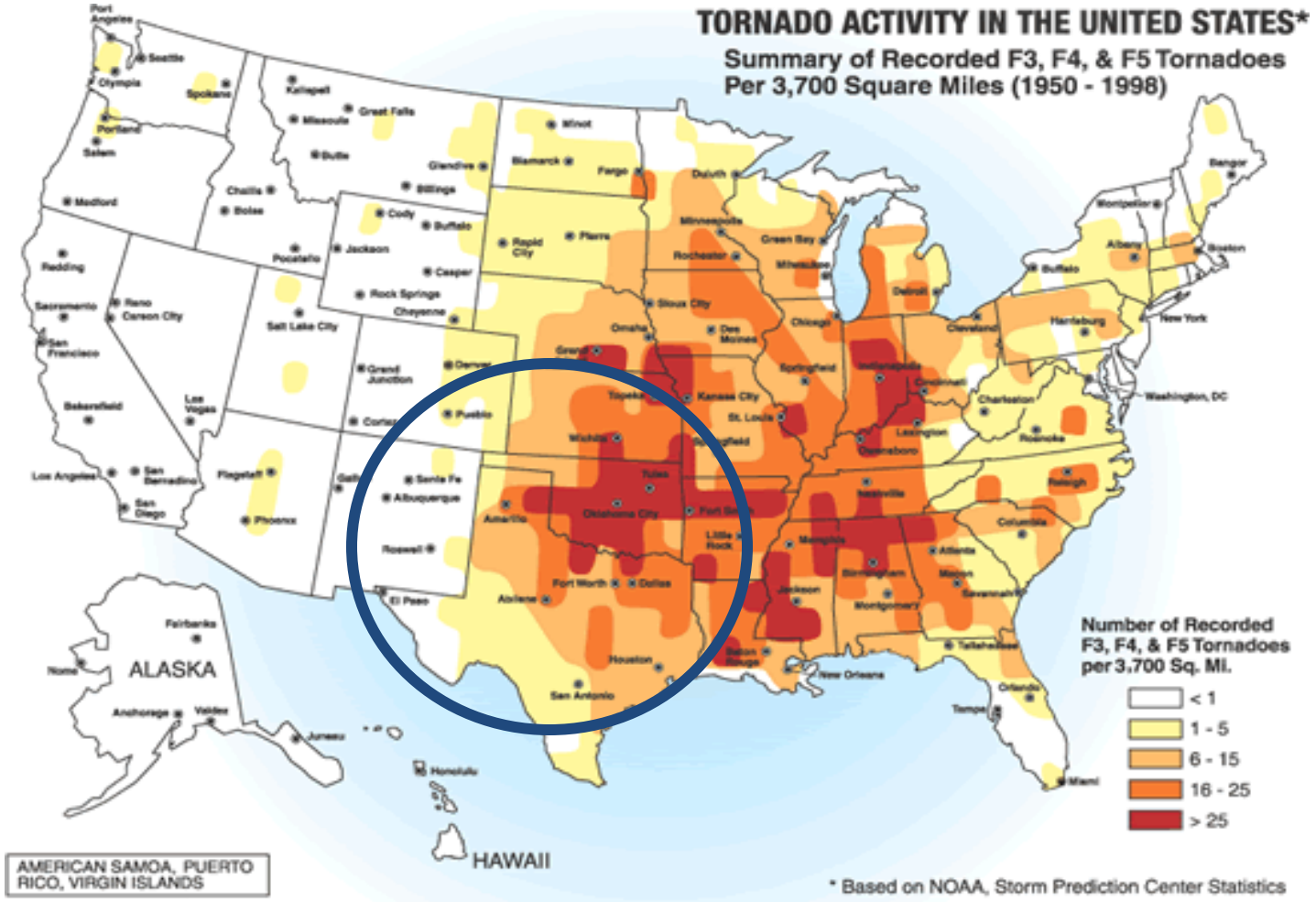


Positive coefficient in wind frequency model – Why?

Low High

T

# Validate Findings Where Possible




* Source: Federal Emergency Management Agency (FEMA) based on National Oceanic and Atmospheric Administration (NOAA) Storm Prediction Center Statistics

# Homeowners Environment Model:

## Components and Examples

- **Weather / Elevation**:
  - Elevation
  - Measures of precipitation
  - Measures of humidity
  - Measures of temperature
  - Measures of wind

- **Proximity :**
  - Commuting patterns
  - Population density
  - PPC

- **Trend / Experience:**
  - Peril's proportion of ISO Loss Cost
  - Trend
  - Amount of insurance

- **Commercial and Geographic Features:**
  - Distance to coast
  - Distance to major body of water
  - Local concentration of types of businesses (e.g., shopping centers)

# Economic Data

# Problem: Identifying Policies to Audit

**What is premium audit?**

- Review of the insured's records to determine the true exposures and correct premium
- Regulatory requirement in WC
- Typically in 30–90 days of policy expiration

**How is it performed?**

- Physical (by a human auditor) – accurate but expensive
- Phone – not very accurate but cost-effective
- Self-report (insured fills and sends a form) – very unreliable

**What are the results?**

- AP – insured owes **additional premium**
- RP – carrier **returns premium** to insured
- Closed-even – no change to premium

# Diverse Data Sources Add Value

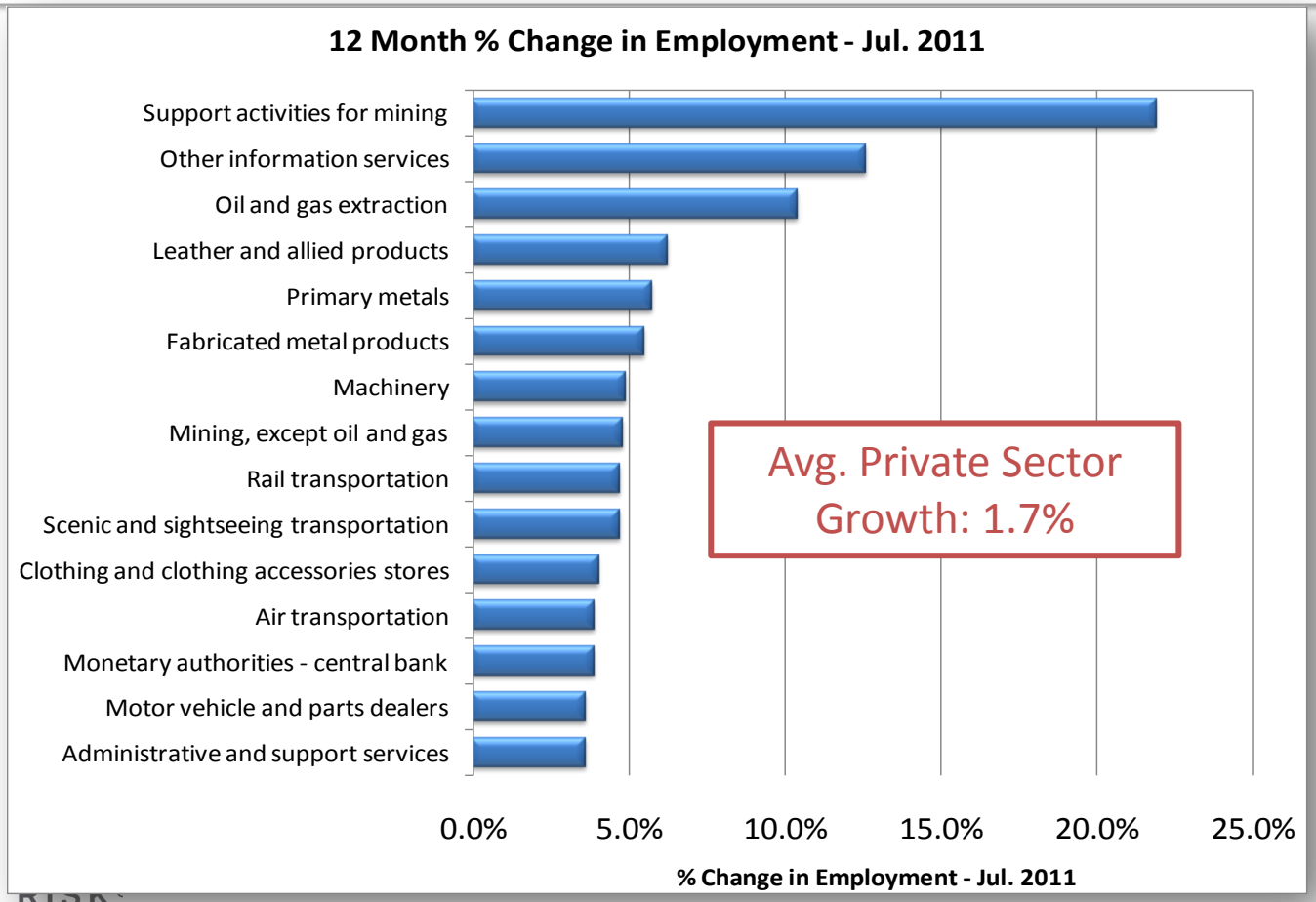
- Federal Reserve
  - Interest rates and money supply
- Bureau of Labor Statistics (BLS)
  - Unemployment statistics
  - Injury, illnesses, and fatalities (IIF)
  - Wages and occupations
- Bureau of Economic Analysis (BEA)
  - Various measures of economic output (GDP)
- Area demographics
  - Census

# Example – Current Employment Survey

- Monthly BLS survey
  - Approximately 140,000 businesses and government agencies representing approximately 410,000 worksites
    - Provides employment, paid hours, and earnings information on a national basis
    - More than 1,100 industries at various levels of aggregation
    - 290 series of seasonally adjusted data
    - 550 special derivative series, such as indexes
- Thousands of features created
  - Ratios, indexes, change over time, change over geography, etc.

# Identify Hot Sectors Early

## Employment growth varies by industry during the economic cycle

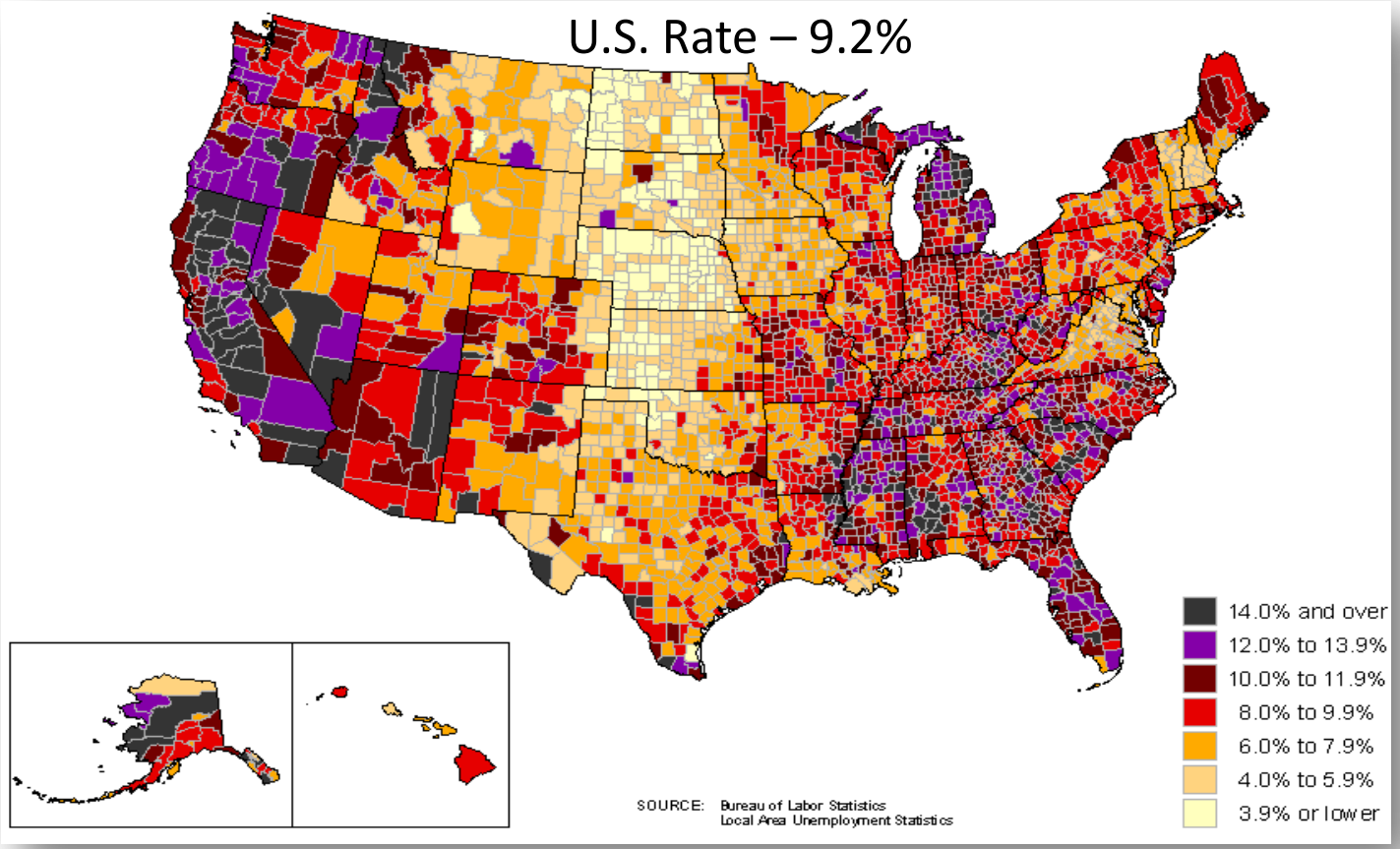



Source: US Bureau of Labor Statistics

# Identify Geographic Effects

Data available at various geographic levels

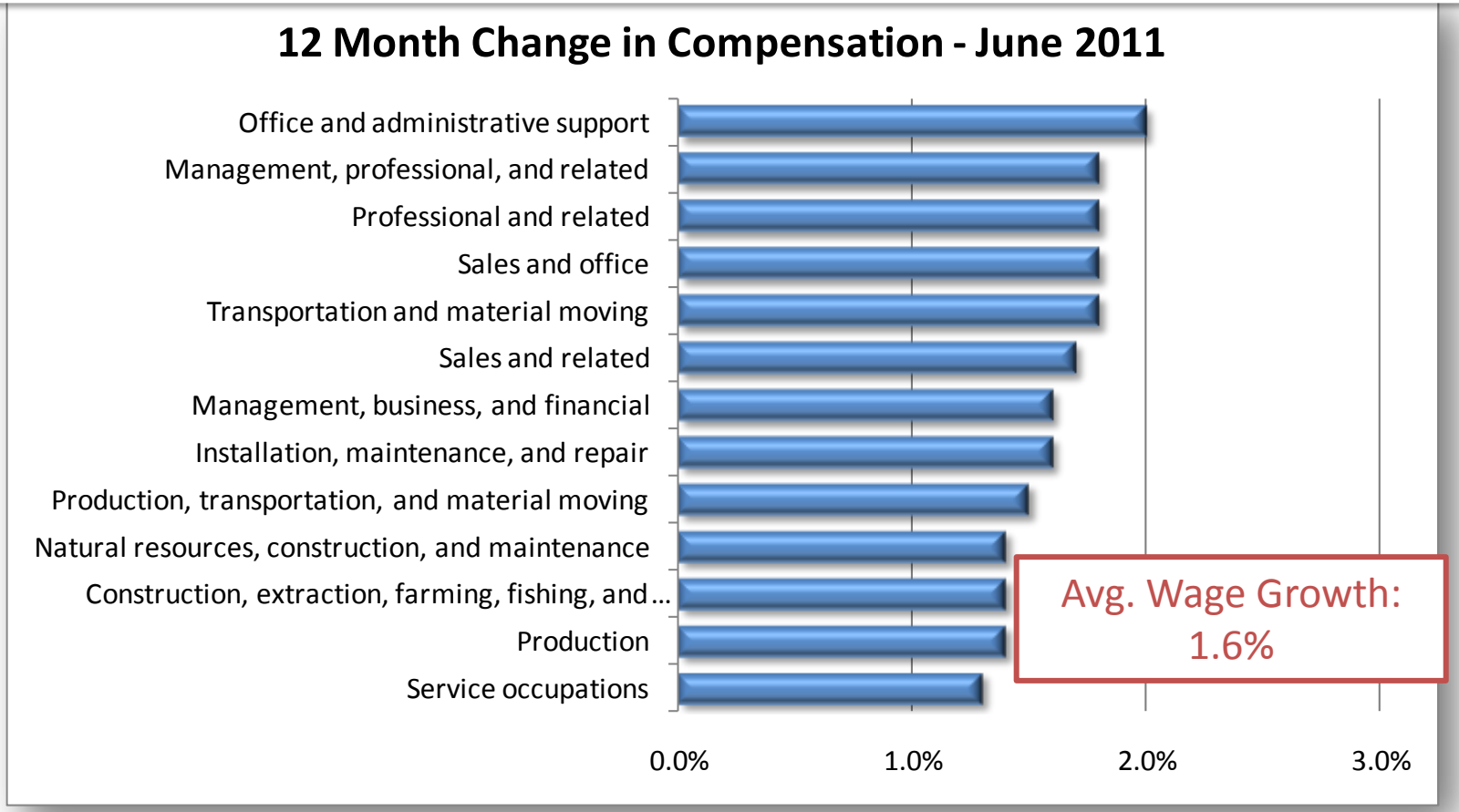
**Unemployment Rate by County – June 2011**




Source: US Bureau of Labor Statistics

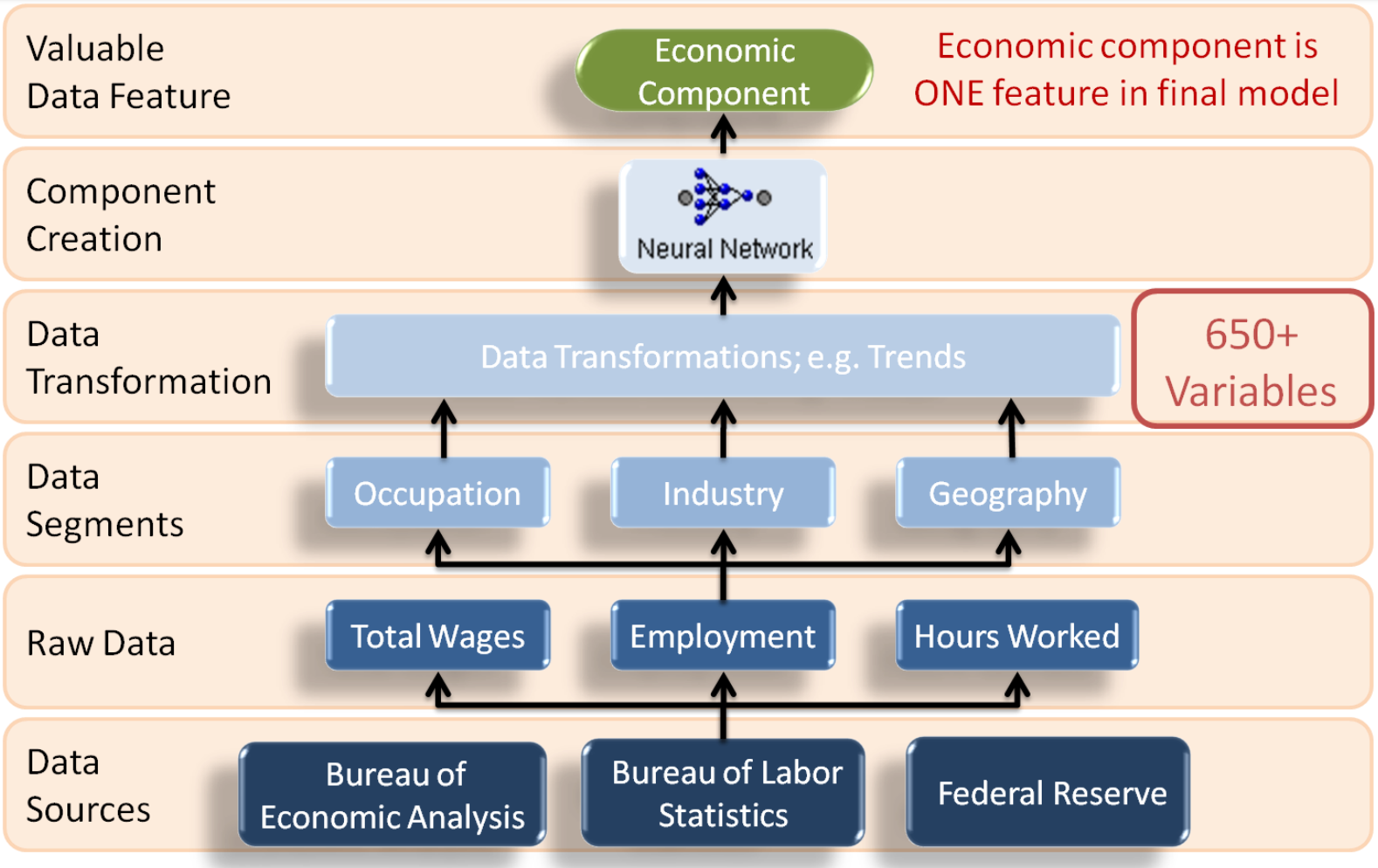
# Wage Growth by Occupation

## Wage growth also varies, adding additional insights

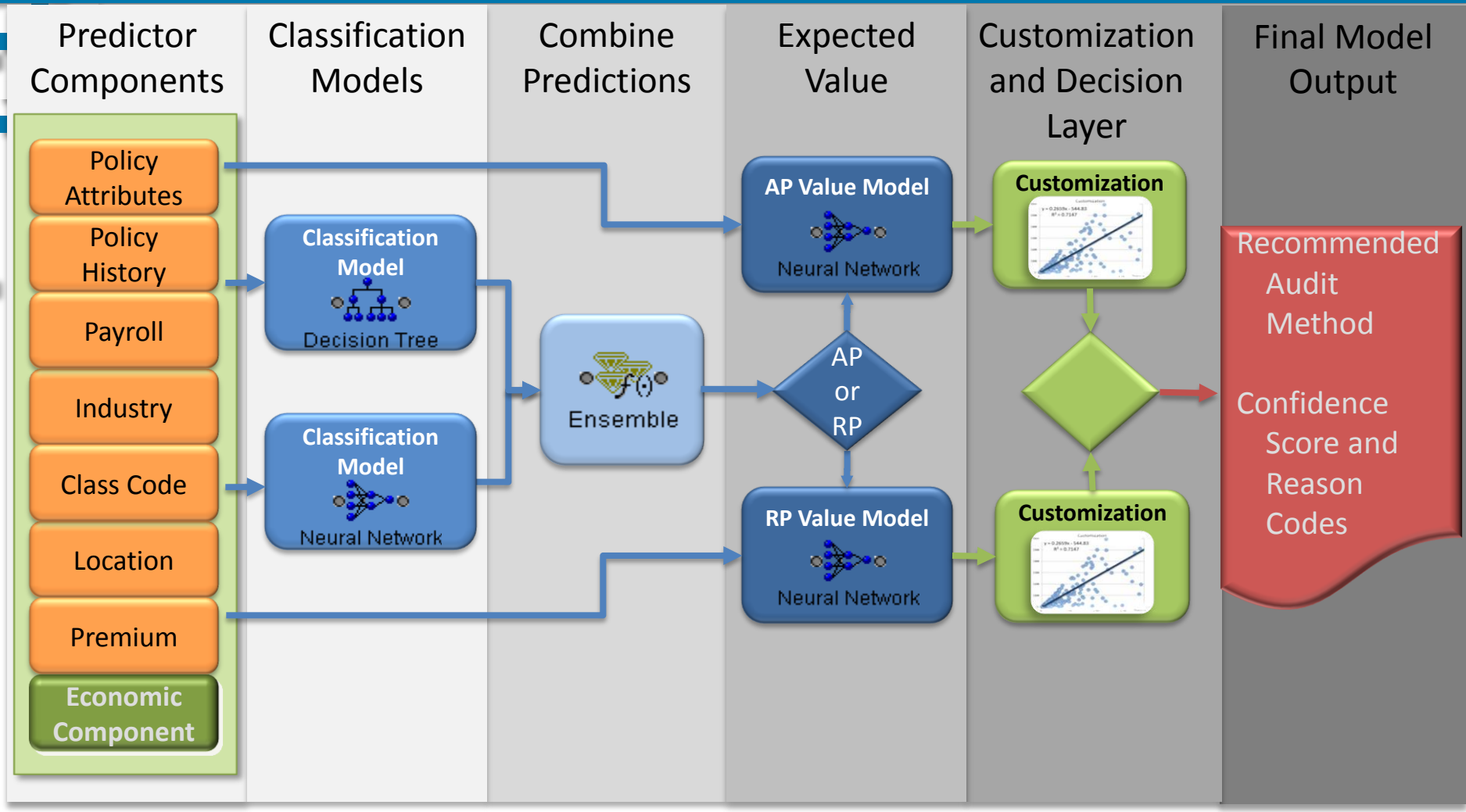



Source: US Bureau of Labor Statistics

# Economic Component



# Audit Selection Model Architecture



# Summary

- Better business decisions are the key to success
  - Analytics can shape decisions, but requires good data
- Raw data is often not very useful
  - Takes time, talent, and tools to extract valuable information from data
- Using packaged *analytic objects* can help fuel innovations quickly and cost-effectively

# Questions?

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