Time Series Analysis

GA DAT3

Agenda

- About Time Series Analysis
- What is Time Series Data
- Common Analysis For Time Series Data

About Time Series Analysis

TIME SERIES ANALYSIS

- In this class, we'll discuss analyzing data that is changing over time.
- In most of our previous examples, we didn't care which data points were collected earlier or later than others.
- We made assumptions that the data was *not* changing over time.
- This class will focus on statistics around data that is changing over time and how to measure that change.

TIME SERIES ANALYSIS

In this lesson, we will focus on Identifying problems related to time series.

Additionally, we will discuss the unique aspects of Mining and Refining time series data.

What is Time Series Data?

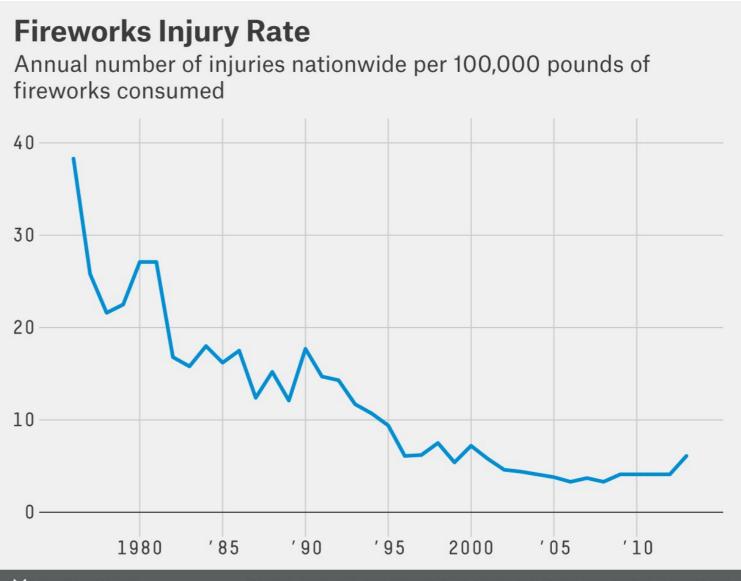
- Time series data is any data where the individual data points change over time.
- This is fairly common in sales and other business cases where data would likely change according to seasons and trends.
- Time series data is also useful for studying social phenomena. For instance, there is statistically more crime in the summer, which is a seasonal trend.

- Most datasets are likely to have an important time component, but typically we assume that it's fairly minimal.
- For example, if we were analyzing salaries in an industry, it's clear that salaries shift over time and vary with the economic period.
- However, if we are examining the problem on a smaller scale (e.g. 3-5 years), the effect of time on salaries is much smaller than other factors, like industry or position.

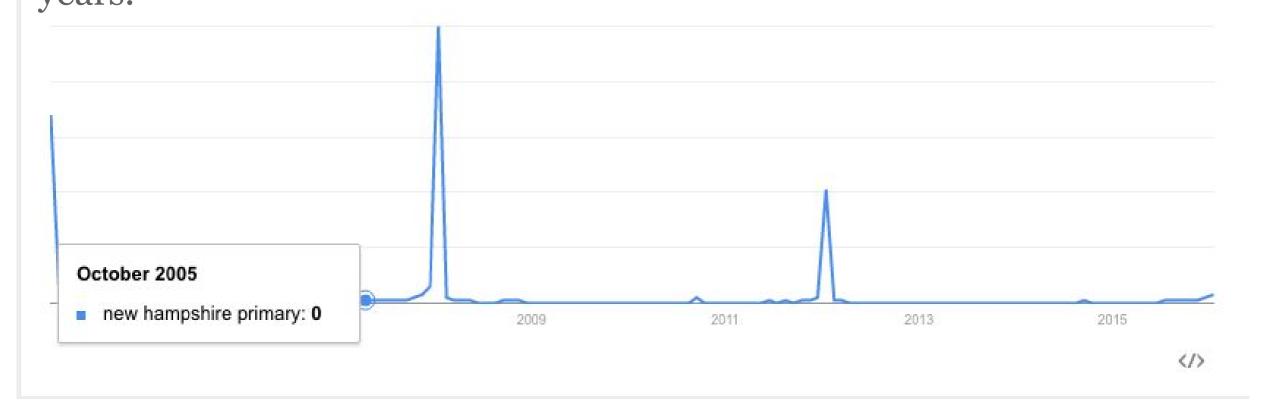
- When the time component *is* important, we need to focus on identifying the aspects of the data that are influenced by time and those that aren't.
- Typically, time series data will be a sequence of values. We will be interested in studying the changes to this series and how related individual values are.
- For example, how much does this week's sales affect next week's? How much does today's stock price affect tomorrow's?

- Time series analysis is useful in many fields: sales analysis, stock market trends, studying economic phenomena, social science problems, etc.
- Typically, we are interested in separating the effects of time into two components:
- Trends significant increases or decreases over time
- Seasonality regularly repeating increases or decreases

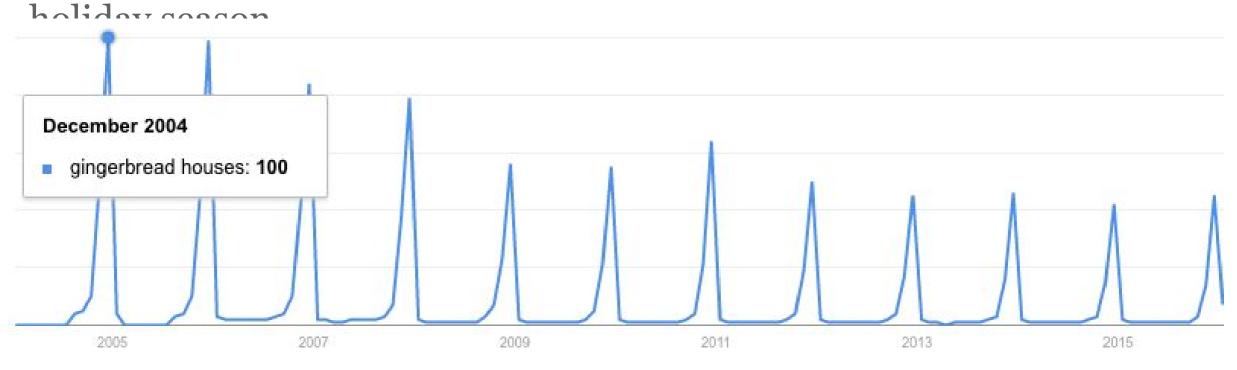
This plot of fireworks injury rates has an overall *trend* of fewer injuries with no *seasonal* pattern.



• Meanwhile, the number of searches for the New Hampshire Primary has a clear *seasonal* component - it peaks every four years and on election years.



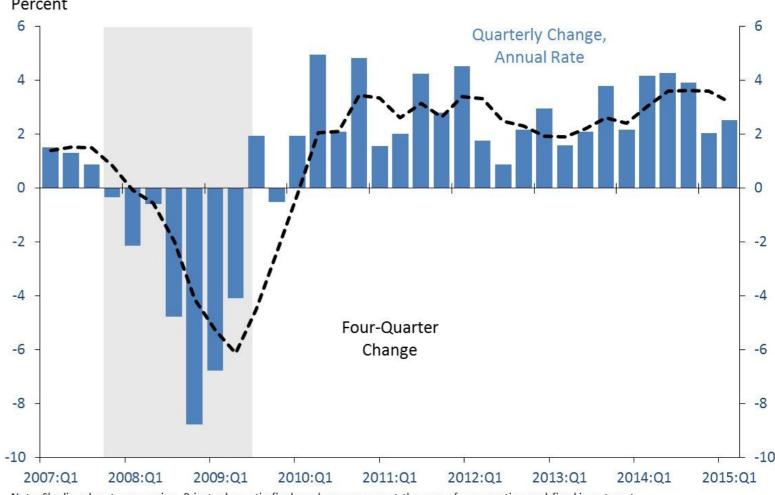
• Similarly, searches for 'gingerbread houses' spike every year around the



• These spikes recur on a fixed time-scale, making them *seasonal* patterns.

Many other types of regularly occurring up or down swings may occur without a fixed timescale or *period* (e.g. growth vs. recession for economic trends).

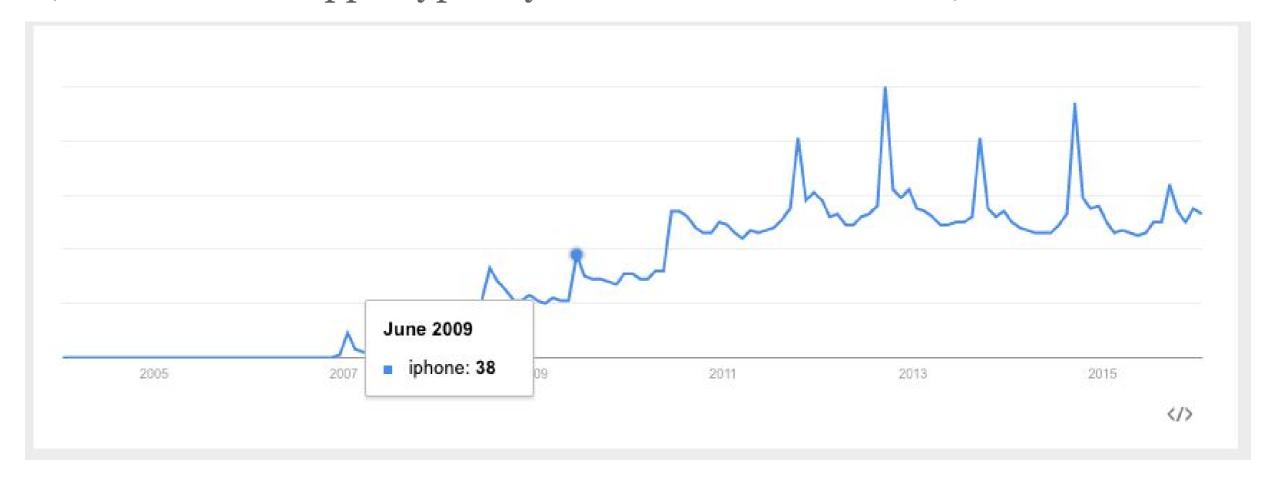
Real Private Domestic Final Purchases Growth, 2007-2015



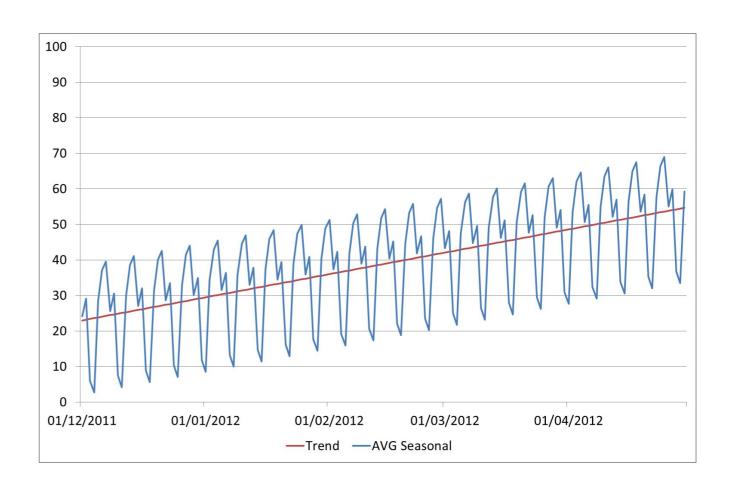
Note: Shading denotes recession. Private domestic final purchases represent the sum of consumption and fixed investment. Source: Bureau of Economic Analysis; CEA calculations.

- These aperiodic patterns are called *cycles*.
- While identifying aperiodic cycles is important, they are often treated differently than seasonal effects. Seasonal effects are useful for their consistency, since prior data is useful as a predictor.

• Searches for "iphone" have both a general trend upwards (indicating more popularity for the phone) as well as a seasonal spike in September (which is when Apple typically announces new versions).



- Most often, we're interested in studying the *trend* and not the *seasonal* fluctuations.
- Therefore it is important to identify whether we think a change is due to an ongoing trend or seasonal change.



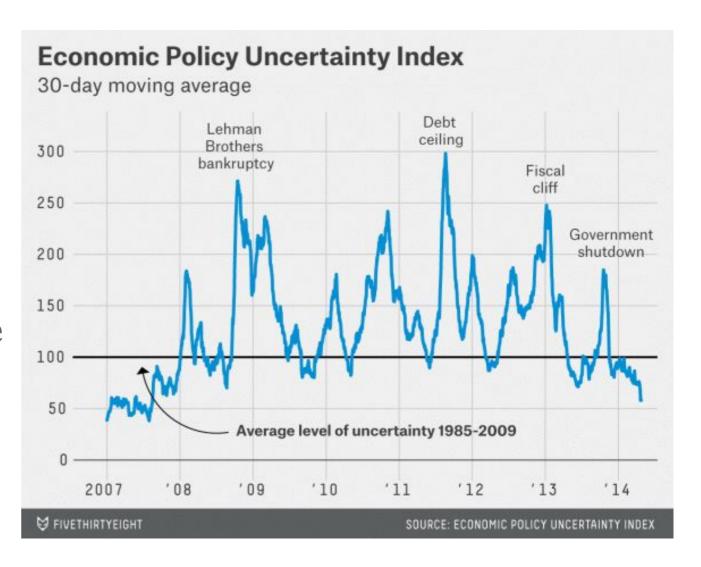
Common Analysis For Time Series Data

- A moving average replaces each data point with an average of *k* consecutive data points in time.
- Typically, this is k/2 data points prior to and following a given time point, but it could also be the k preceding points.
- These are often referred to as the "rolling" average.
- The measure of average could be mean or median.
- The formula for the rolling *mean* is

$$F_t = \frac{1}{p} \sum_{k=t}^{t-p+1} Y_k$$

- A rolling mean would average all values in the window, but can be skewed by outliers (extremely small or large values).
- This may be useful if we are looking to identify atypical periods or we want to evaluate these odd periods.
- For example, this would be useful if we are trying to identify particularly successful or unsuccessful sales days.
- The rolling median would provide the 50 percentile value for the period and would possibly be more representative of a "typical" day.

- This plot shows the 30-day moving average of the Economic Uncertainty Index.
- Plotting the moving average allows us to more easily visualize trends by smoothing out random fluctuations and removing outliers.



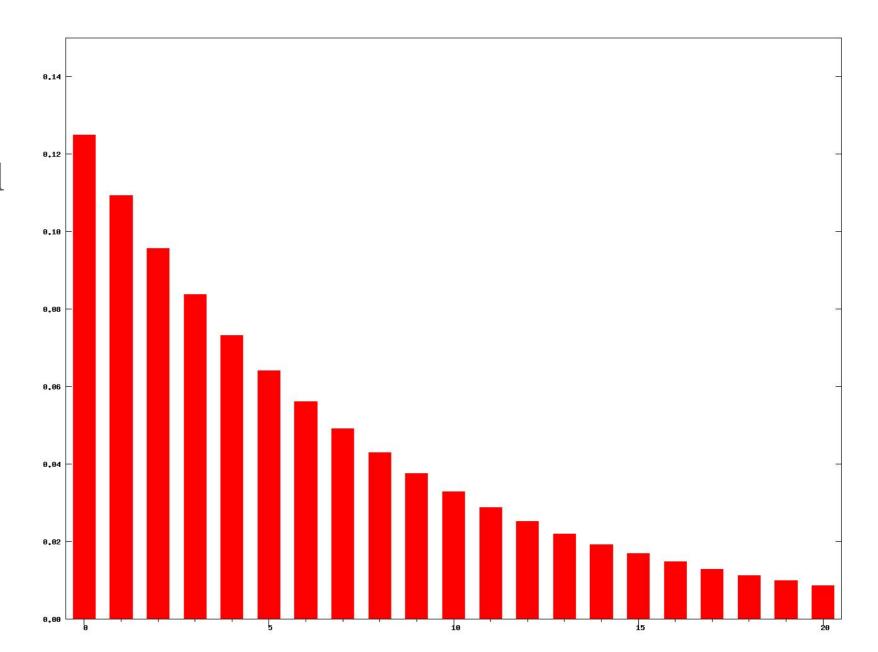
- While this statistic weights all data evenly, it may make sense to weight data closer to our date of interest higher.
- We do this by taking a *weighted moving average*, where we assign particular weights to certain time points.
- Various formulas or schemes can be used to weight the data points.

- A common weighting scheme is an *exponential weighted moving* average (EWMA) where we add a *decay* term to give less and less weight to older data points.
- The EWMA can be calculated recursively for a series Y.

For
$$t = 1$$
, $EWMA_1 = Y_1$

For
$$t > 1$$
, $EWMA_t = \alpha \cdot Y_t + (1 - \alpha) \cdot EWMA_{t-1}$

The weights for an exponential weighted moving average with k = 15.



AUTOCORRELATION

In previous classes, we have been concerned with how two variables are correlated (e.g. height and weight, education and salary).

* Autocorrelation is how correlated a variable is with itself. Specifically, how related are variables earlier in time with variables later in time.

AUTOCORRELATION

To compute autocorrelation, we fix a "lag" *k*. This is how many time points earlier we should use to compute the correlation.

A lag of 1 computes how correlated a value is with the prior one. A lag of 10 computes how correlated a value is with one 10 time points earlier.

AUTOCORRELATION

• The following formula can be used to calculate autocorrelation.

$$r_{k} = \frac{\sum_{t=k+1}^{n} (y_{t} - \bar{y})(y_{t-k} - \bar{y})}{\sum_{t=1}^{n} (y_{t} - \bar{y})^{2}}$$

Conclusion

CONCLUSION

- We use time series analysis to identify changes in values over time.
- We want to identify whether changes are true trends or seasonal changes.
- Rolling means give us a local statistic of an average in time, smoothing out random fluctuations and removing outliers.
- Autocorrelations are a measure of how much a data point is dependent on previous data points.

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