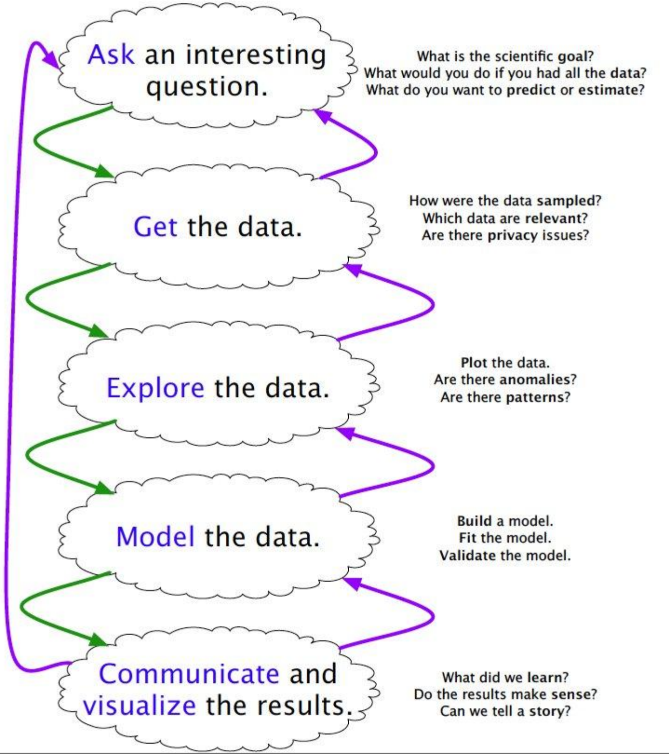
CSE 519: Data Science
Steven Skiena
Stony Brook University

Lecture 13: Building Models

The Data Science Analysis Pipeline

Modeling is the process of encapsulating information into a tool which can make forecasts/predictions.

The key steps are building, fitting, and validating the model.



Philosophies of Modeling

We need to think in some fundamental ways about modeling to build them in sensible ways.

- Occam’s Razor
- Bias-Variance tradeoffs
- Nate Silver: The Signal and Noise

Occam's Razor

This philosophical principle states that "the simplest explanation is best".

With respect to modeling, this often means minimizing the parameter count in a model.

Machine learning methods like LASSO/ridge regression employ penalty functions to minimize features, but also do a "sniff test".

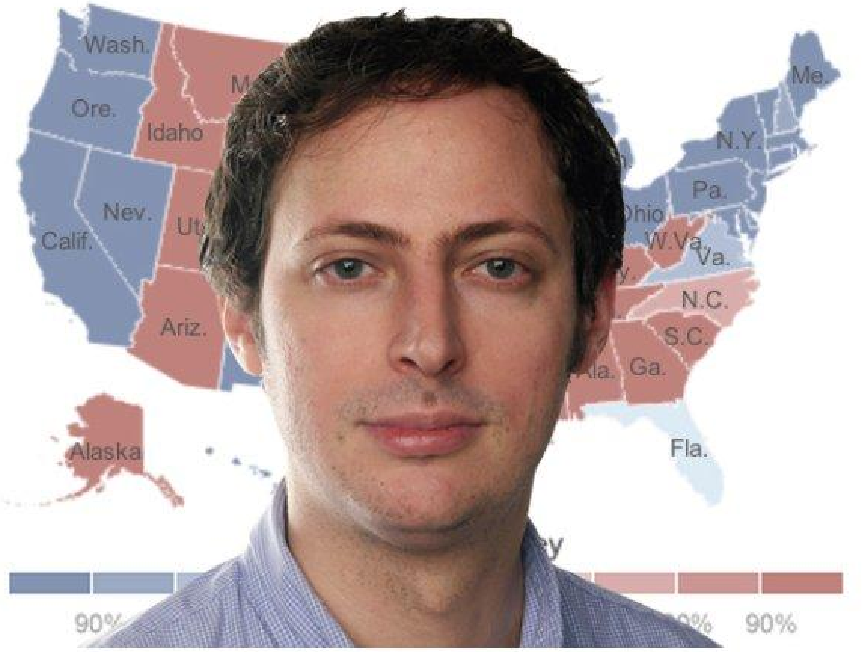
Bias-Variance Tradeoffs

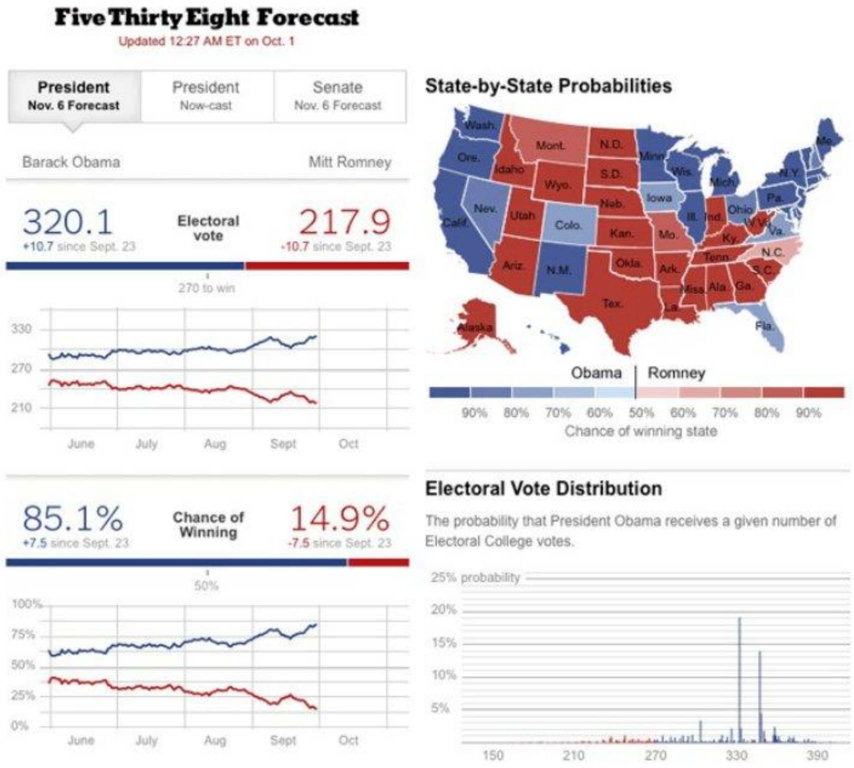
"All models are wrong, but some models are useful."
– George Box (1919-2013)

- *Bias* is error from erroneous assumptions in the model, like making it linear. (underfitting)
- *Variance* is error from sensitivity to small fluctuations in the training set. (overfitting)

First-principle models likely to suffer from bias, with data-driven models in greater danger of overfitting.

What would Nate Silver do?





Principles of Nate Silver

- Think probabilistically
- Change your forecast in response to new information.
- Look for consensus
- Employ Baysian reasoning

The Output of Your Models

Demanding a single deterministic “prediction” from a model is a fool’s errand.

Good forecasting models generally produce a probability distribution over all possible events.

Good models do better than baseline models, but you could get rich predicting if the stock market goes up/down with $p>0.55$.

Properties of Probabilities

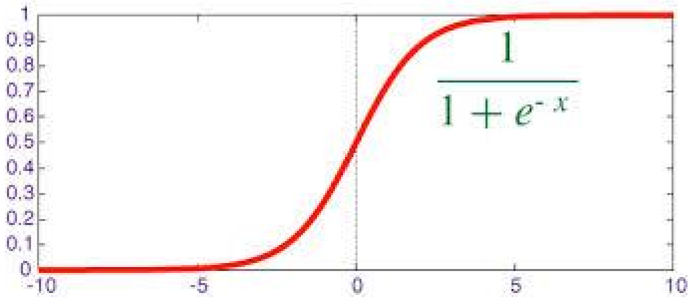
- They sum to 1.
- They are never negative.
- Rare events do not get probabilities of zero.

Probabilities are a measure of humility in the accuracy of the model, and the uncertainty of a complex world.

Models must be honest in what they do/don't know.

Scores to Probabilities

The logit function maps scores into probabilities using only one parameter.



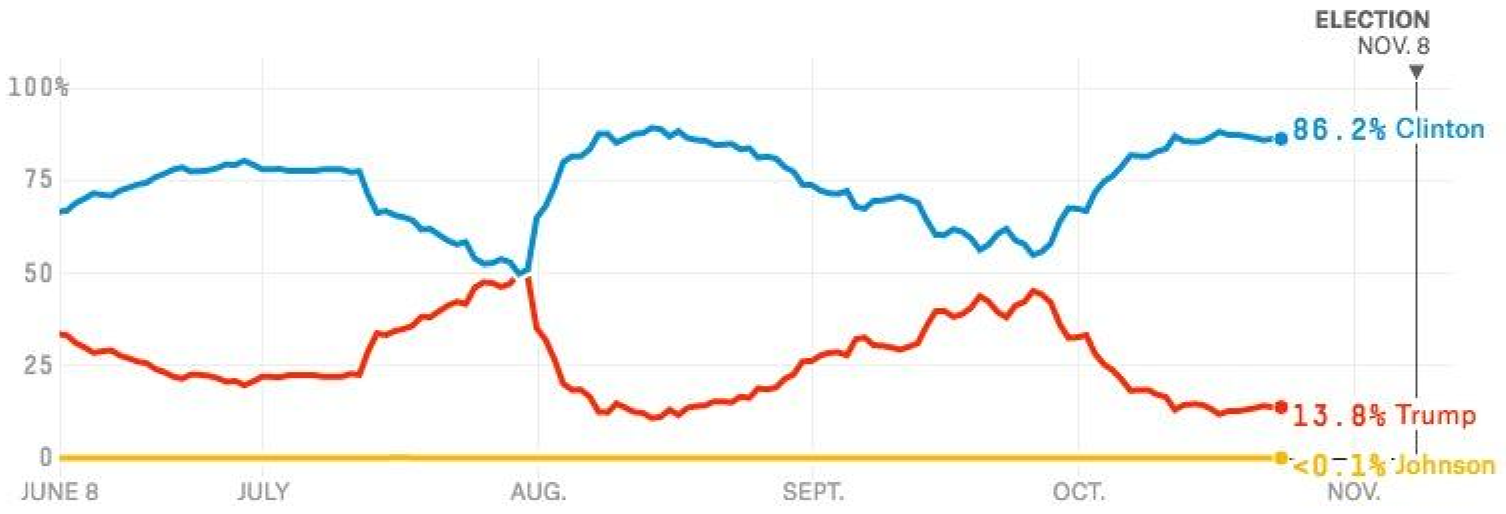
Summing up the “probabilities” over all events s defines the constant *1/s* to multiply each so they sum up to 1.

Live Models

A model is *live* if it continually updating predictions in response to new information.

- Does the forecast ultimately converge on the right answer?
- Does it display past forecasts so the user can judge the consistency of the model?
- Does the model retrain on fresher data?

Presidential Election Forecast, 2016



Look for Consensus

- Are there competing forecasts you can compare to, e.g. prediction markets?
- What do your baseline models say?
- Do you have multiple models which use different approaches to making the forecast?

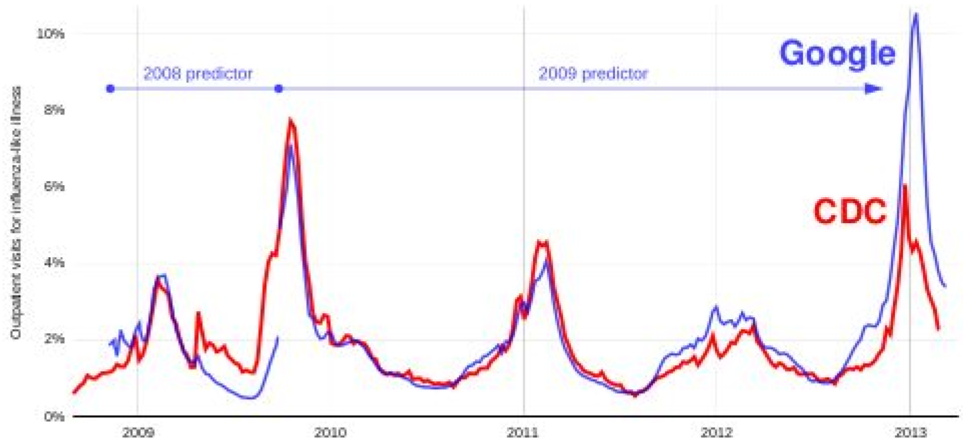
Boosting is a machine learning technique which explicitly combines an ensemble of classifier.

Google Flu Trends

Predicted flu outbreaks using query frequency of illness terms.

The model failed after Google added search suggestions

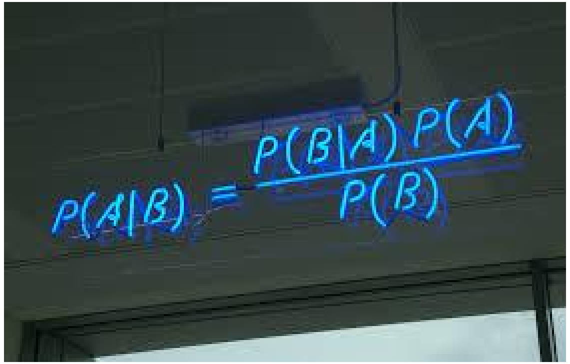
Second divergence in 2012–2013 for U.S.

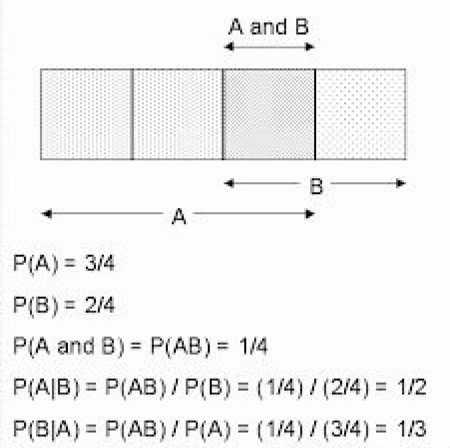


Bayesian Reasoning

Bayes' Theorem lets us update our confidence in an event in response to fresh evidence.

Bayesian reasoning reflects how a **prior** probability P(A) is updated to given the **posterior** probability P(A|B) in the face of a new observation B according to the ratio of the **likelihood** P(B|A) and the **marginal** probability P(B)





Steps to Build Effective Models

- Identify the best output type for your model, likely a probability distribution.
- Develop reasonable baseline models.
- Identify the most important levels to build submodels around.
- Test models with out-of-sample predictions.

Modeling Methodologies

- First principle models: based on a theoretical explanation of how the system works (like simulations, scientific formulae)
- Data-driven models: based on observed data correlations between input parameters and outcome variables.

Good models are typically a mixture of both.

Principled or Data Driven? (Projects)

- Miss Universe?
- Movie gross?
- Baby weight?
- Art auction price?
- Snow on Christmas?
- Super Bowl / College Champion?
- Ghoul Pool?
- Future Gold / Oil Price?

Baseline Models

"A broken clock is right twice a day."

The first step to assess whether your model is any good is to build baselines: the simplest *reasonable* models to compare against.

Only after you decisively beat your baselines can your models be deemed effective.

Representative Baseline Models

- Uniform or random selection among labels.
- The most common label in the training data.
- The best performing single-variable model.
- Same Label as the previous point in time.
- Rule of thumb heuristics.

Baseline models must be fair: they should be simple but not stupid.

Project Baseline Models

- Miss Universe?
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Taxonomy of Models

Models have different properties inherent in how they are constructed:

- Linear vs. non-linear
- Discrete vs. continuous models
- Black box vs. descriptive
- Stochastic vs. deterministic
- Flat vs. heirarchical

Discrete vs. Continuous Models

Discrete models manipulate discrete entities.

Representative are discrete-event simulations using randomized (Monte Carlo) methods.

Continuous models forecast numerical quantities over reals. They can employ the full weight of classical mathematics: calculus, algebra, geometry, etc.

General vs. Ad Hoc Models

Machine learning models for classification and regression are general, meaning they employ no problem-specific ideas, only specific data.

Ad hoc models are built using domain-specific knowledge to guide their structure and design.

Data science generally seek general models, but I think ad hoc models can be better.