STK-INF 4000 - Week 16

Leftovers & Recap

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Google's Rules of ML

Source: http://martin.zinkevich.org/rules_of_ml/rules_of_ml.pdf.

0. Before Machine Learning
1. ML Phase 1: Your First Pipeline
2. ML Phase 2: Feature Engineering
3. ML Phase 3: Slowed Growth, Optimization Refinement, and Complex Models

Before ML

- Don't be afraid **not** to use ML!
  - Heuristics might work well.
  - You might not have enough data for ML.
- Design and implement metrics first.
  - Easier to get user consent early.
  - Start collecting data early.
  - Better system design if data collection built in.
  - Notice what changes and what doesn't.
- Prefer ML over complex heuristics.

ML Phase 1: Your First Pipeline

- Focus on infrastructure first.
  - Keep models simple.
  - Think about integration of ML part into system.
  - Use simple features.
- Test infrastructure independent from model.
- Be careful when copying pipelines.
  - E.g. dropping historical data.
- Re-use heuristics.
  - Preprocessing.
    - E.g. drop blacklisted domains.
  - Use heuristic as features.
  - Use heuristic's inputs as features.
  - Modify feature using heuristic.

Monitoring

- How often do we need to re-train?
- Test models before exporting.
    - Don't export models with e.g. bad AUC.
- Beware of silent failures.
    - E.g. input table not getting updated.
- Document features.
- Make people responsible for features.

Your first Objective

- Don't overthink your fist choice of *objective*.
- Choose a simple and observable metric as first objective.
  - Good
    - Did the user click?
    - Did the company go bankrupt?
  - Maybe not at first
    - Did the user come back the next day?
    - How long did the user visit?
  - Bad
    - Is the user happy?
- Start with interpretable models.
- Don't combine tasks.
  - E.g. quality ranking + spam filtering.

Phase 2: Feature Engineering

- Plan for iterations.
  - Don't be afraid to launch a model that's *just* good enough.
  - Don't be afraid to spend a little time on a model.
- Don't start out with learned features.
  - E.g. clustering, deep learning.
- Prefer features that are generic.
  - E.g. 'like count' makes *only* sense for older Tweets.
- Don't be afraid of features only applying to few cases.
  - If you have enough data.
  - Can use regularization to remove too specific features.
- Combine and modify features.
  - E.g. discretization, cross-products.
- Rule of thumb for linear models: $d = O(N)$.
  - Of course, provided enough computing power.
- Clean up you feature space.
  - Unused features incur costs!

Human Analysis

- Beware of you biases!
- Measure difference between models.
- Utility is more important than predictive power.
  - What do you use or model for?
  - How good is it at that.
  - If they diverge, re-think model objective.
- Look for patterns in errors.
  - Create features to overcome them.
- Quantify any issues with the model.
  - First measure, then optimize.
- Same short term behavior $\neq$ same long-term behavior.

Training Serving Skew

- Why?
  - Differences in pipelines.
  - Difference in data patterns at serving time.
  - Feedback loops.
- Save serving data + outcomes for later training.
- Sample and weight, don't drop data.
- Beware of changing external factors.
  - E.g. table with weather data.
- Re-use code as much as possible.

Training Serving Skew

- Choose test data for time series data with care!
  - Don't just leave data out randomly.
- Take care when using binary classification for filtering.
  - False positives can't be used for training straight-forwardly.
  - Better: Hold out e.g. 1% of data an let it all pass.
- Ranking = Skew
- Beware of feedback.
  - E.g. higher rank $\rightarrow$ more clicks.
- Measure skew.

Phase 3: Refinement

- Check if you're still optimizing the right thing.
  - Even great features won't save you if you don't!
- Keep the big picture in mind.
- Don't be afraid of ensembles.
  - But keep them simple!
- When performance plateaus, look for new data sources.
  - Don't waste too much time on refining models.
- Personalization $\neq$ popularity!
- Personalization $\neq$ personalization!
  - People have same peer group across platforms. Not necessarily same tastes.

What We have Learned...

Moore's Law

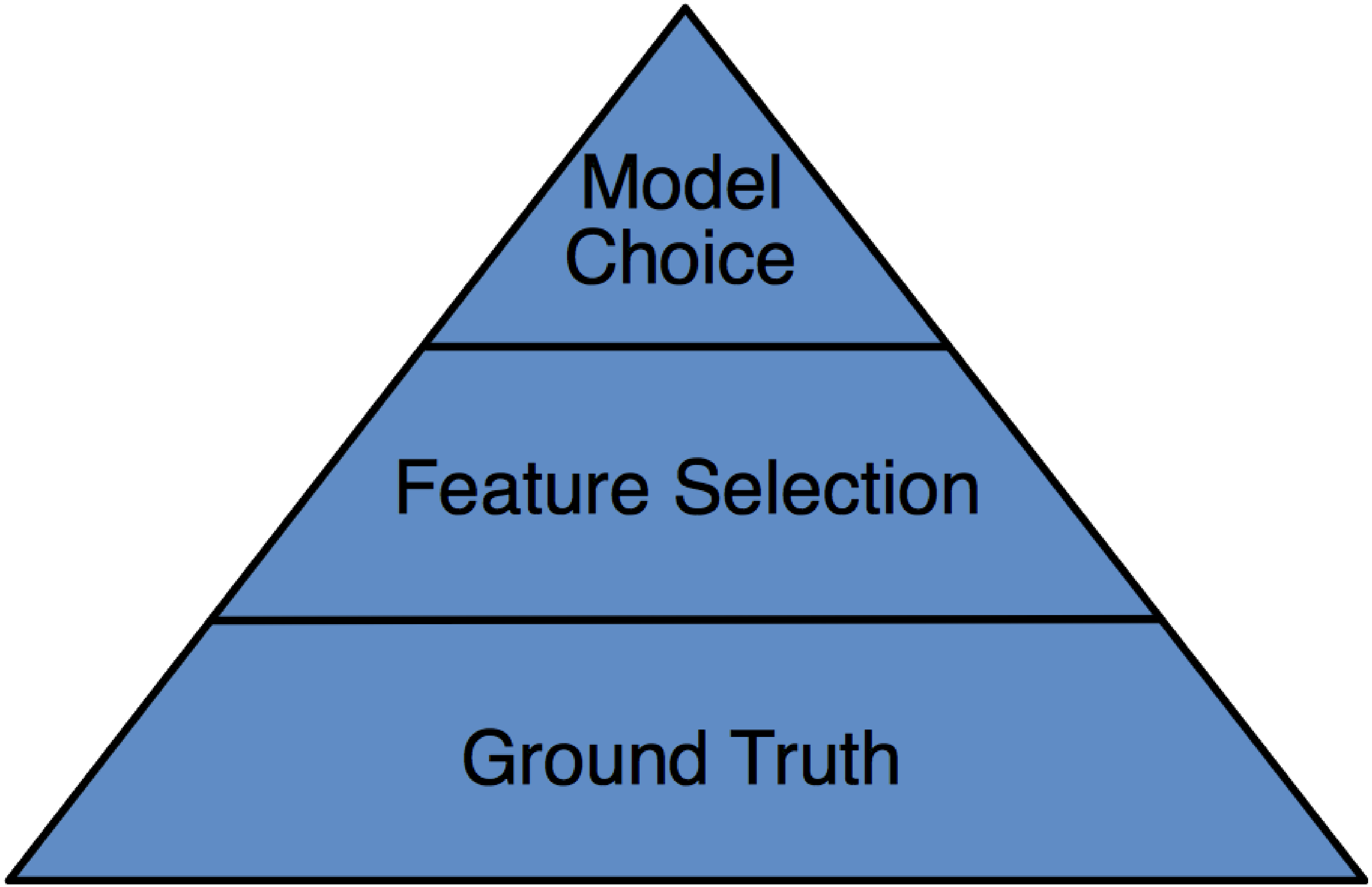
By Wgsimon - Own work, Wikimedia

By Wgsimon - Own work, Wikimedia

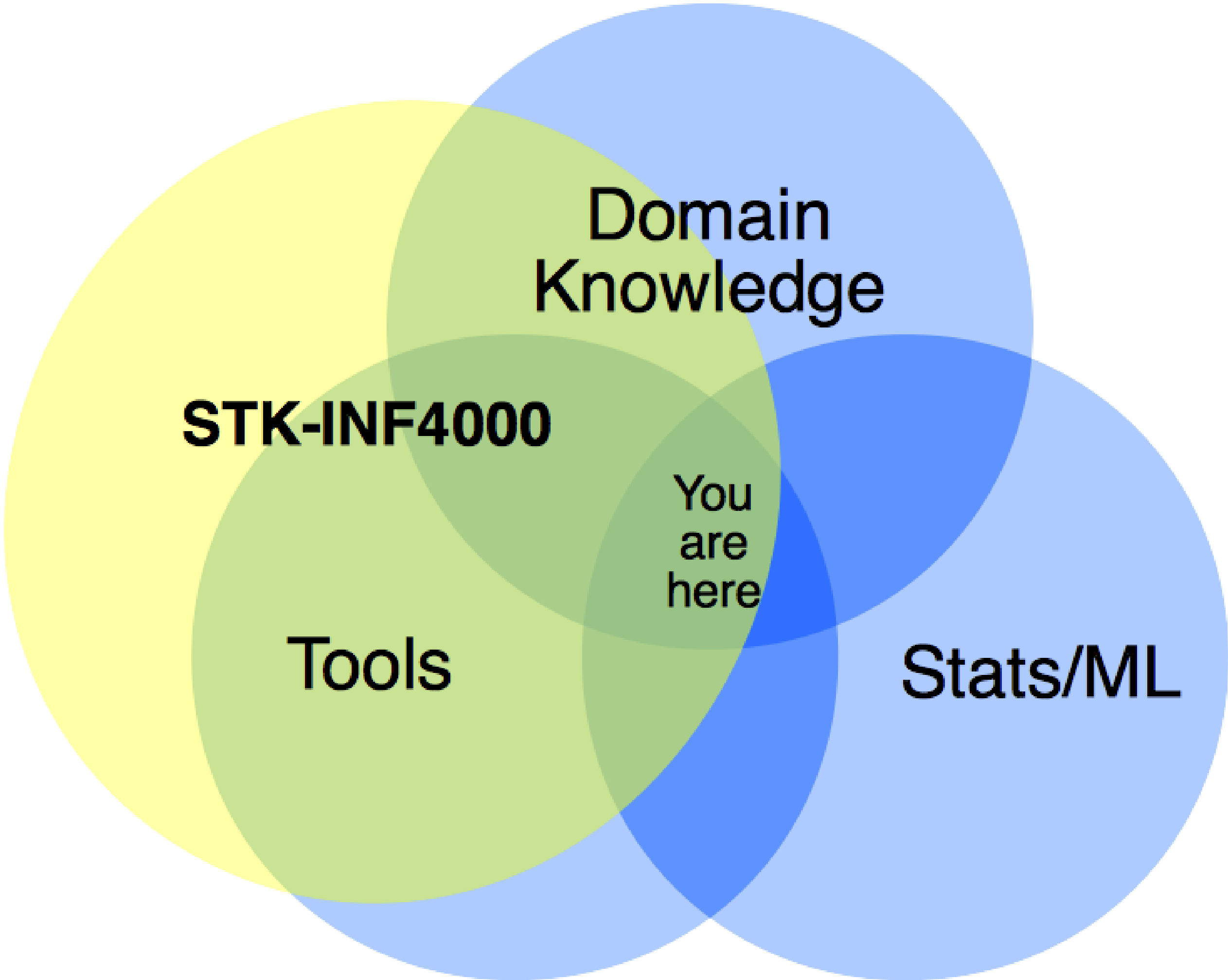
Tools

Apache Foundation

Tools ... aren't everything



The Idea



Course Content

Python

- Lists
  - Utility Functions
  - List comprehensions
  - Element access
  - Combining lists
- Tuples
- Strings
- `for` loops
  - `for-else`
- `while` loops
- Reading data
- Lambdas
- Plotting basics

More Python

- Functions
    - Default arguments
    - `*vargs`, `**kwargs`
- Dictionaries
    - Utility Functions
    - Element access
    - Dict comprehensions
    - `defaultdict`, `Counter`
- Decorators
- Objects
    - Methods
    - Inheritance
- JSON

Web scraping

- Scrapy
- Beautifulsoup

Testing & IO

- Unittests
  - What can & can't be tested?
- REST APIs
- Twitter
  - Search API
  - Streaming API
  - Authentication
- MongoDB
  - Storing
  - Retrieving
  - Modifying
  - Aggregation

Machine Learning

- Intro
  - Data, input, target.
  - Learning task
  - Types of data
  - Supervised & Unsupervised learning
- Basic probability
  - Expectation values
  - Probability distributions
  - Conditional probability
- Decision theory
  - $f(x) = \mathrm{E}(Y|X = x)$.
  - Loss function.
- K-Nearest neighbors
  - Bias-variance tradeoff

Pandas

- Series
- Index
- Arithmetic
- Data Frames
- Aggregation
- Pivot/Stack
- Reading data
- Plotting

Linear Regression

- Linear approximation
- Confidence intervals on parameters
- z-Score
- F statistic
- In Python
  - Pure Numpy
  - Scikit-Learn
  - Statsmodels

Variable Selection

- All subsets
- Forward/backward step-wise
- Shrinkage methods
  - Lasso
  - Ridge regression
  - Elastic net

Big(er) Data Quantities

- What is big?
- Inner workings of a computer.
- Storage
  - Latency
  - Bandwidth
  - Size
- CPU speeds
- Clusters

Map Reduce

- By hand.
- Spark.
  - RDDs
    - map, reduce, take, aggregate, (-by key), ...
  - Reading data

Classification

- Decision boundaries.
- Linear classification.
- Discriminant function.
- Categorical inputs.
- Linear/Quadratic Discriminant Analysis.
    - Regularization.
- Logistic regression.
- Objectives
    - False/true positives/negatives
    - Sensitivity, Specificity, Precision, Accuracy.
    - ROC, AUC
- Cover type data set.
- Wine quality data set.

Classification in Spark

- The Spark Data Frame.
  - Operations
  - Creating
  - Selecting data
  - Schema
- Spark ML

Anomaly Detection

- Rule-based systems.
- Outliers, z-score, Chebychev's inequality.
- Clustering
  - Objective, distance functions, Linkage.
  - Hierarchical clustering.
    - Divisive vs. agglomerative.
  - K-Means and others.
  - Knee method and inertia
- Clustering for fraud detection.

Clustering in Spark

- Data frames.
  - Collecting features.
  - Exporting to pandas.
- Clustering in Spark ML

Trees

- Calculating trees.
  - Stopping criteria.
- Regression and classification trees.
- Trees vs. regression.
- Bias-Variance trade-off, again.
  - Train-test split.
- Split functions
  - Misclassification: $1 - \hat{p}_{mk(m)}$.
  - Gini index: $\sum_{k=1}^{K} \hat{p}_{mk}(1 - \hat{p}_{mk})$.
  - Cross-entropy: $-\sum_{k=1}^{K} \hat{p}_{mk} \log \hat{p}_{mk}$.
- Loss matrix.

Ensembles and Boosting

- Forward step-wise additive modeling.
- Adaboost.
- Loss functions
  - Classification
    - Misclassification: $I(\text{sign}(f) \neq y)$.
    - Exponential: $\exp(-yf)$.
    - Binomial: $\log(1 + \exp(-2fy))$.
    - Squared error: $(y - f)^2$.
  - Regression
    - Squared error, $(f(x) - y)^2$.
    - Absolute error, $|f(x) - y|$.
    - Huber loss,

$$L(f(x), y) = \begin{cases} (y - f(x))^2 & \text{if } |y - f(x)| \leq \delta \\ 2\delta|y - f(x)| - \delta^2 & \text{else.} \end{cases}$$

Gradient boosting

- Gradient descent.
- Fitting gradient descent with trees.
- Advantages:
  - Can use most loss functions.
  - Can use regularization.

Time series

- ARMA models.
- For outlier detection.

Model Evalutation

- Test error.
- Expected prediction error.
- Training error.
- Hyperparameters.
- Closer look at the bias.
  - Model bias
  - Estimation bias
- Generalization error, Akaike IC
- Cross Validation
  - How many folds?
- Bootstrapping.
- Bagging.
- Random forests.

Pipelines

- In Spark.
- In Sklearn.
- Including validation.
- Parameter tuning in pipelines.

NLP Field Trip

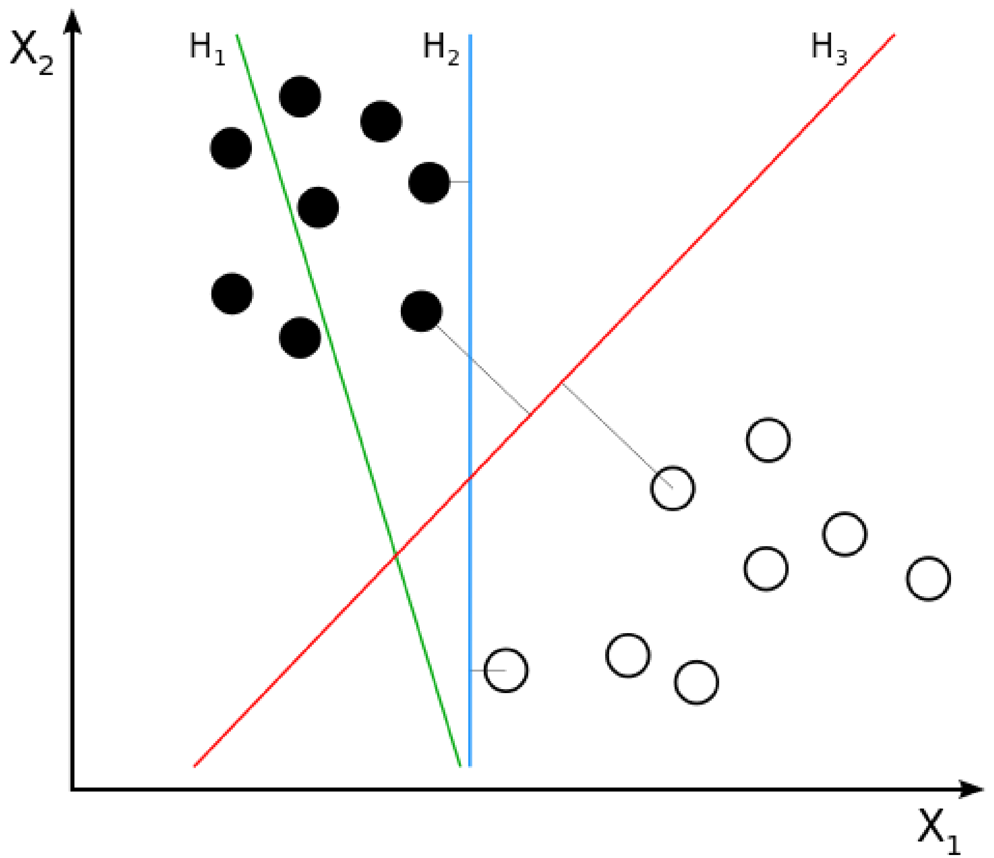
- Types of NLP tasks.
- Regular expressions.
- Tokenization.
- Normalization.
    - Stemming.
    - Lemmatization.
- Language models.
    - Markov assumption.
    - N-Gram models.
    - Calculating N-Gram probabilities.
- Text classification.
    - Naïve Bayes.

Presenting Results

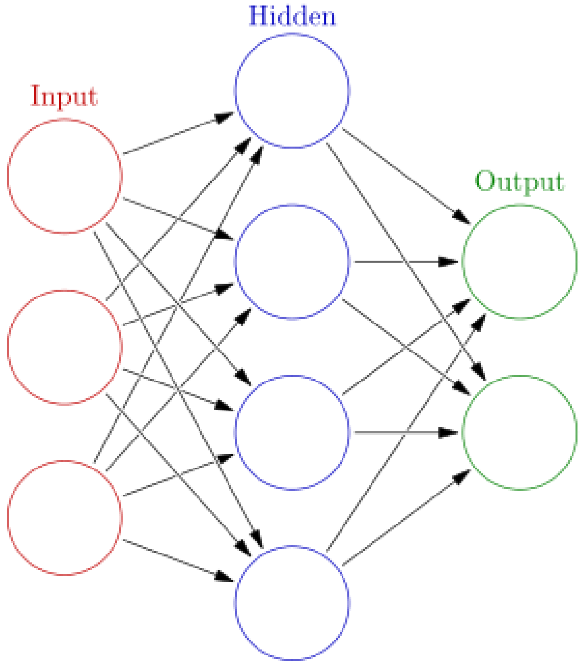
- Flask.
- Javascript.
    - Google charts.

What's missing?

Support Vector Machines



Neural Networks



The Cloud

- AWS
- Google Cloud
- Azure
- Bluemix

Where to go From Here?

- NLP
- Deep Learning
- Machine Learning
- Summer Jobs
- Master Thesis in Industry

Final Presentation

- Don't forget an introduction!
  - What's your goal?
  - What's the main idea?
- Have you solved you original problem?
  - If not, where are you?
  - Is this enough for some intermediate goal?
- Practical issues.
  - Pipelines.
  - Will you need to scale (Spark)?
- Show what you've done since last time.