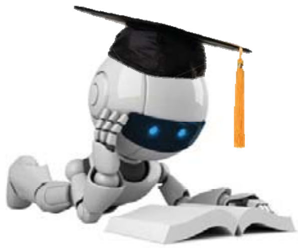


# Advice on Applying ML

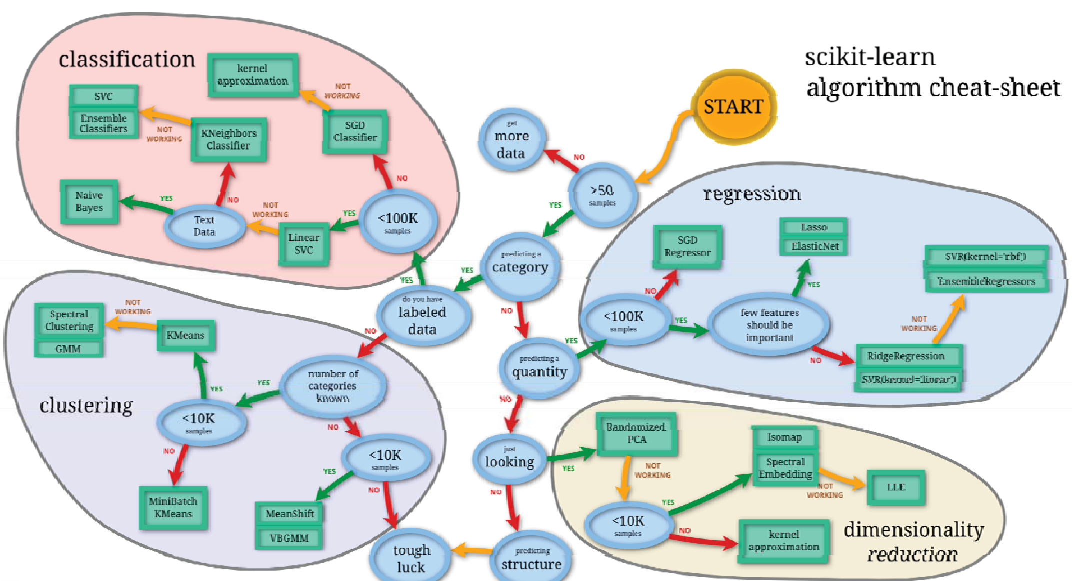

xkcd, Machine Learning

Instructor: Jessica Wu -- Harvey Mudd College

The instructor gratefully acknowledges Andrew Ng (Stanford), from whom these slides are adapted.



# Choosing the Right Estimator




Back

http://scikit-learn.org/stable/tutorial/machine_learning_map/

# Today's Lecture

- Advice on applying learning algorithms to different applications
- Most of today's lecture is not very mathematical…
  - but it is also some of the hardest material in this class to understand
- Some of what I will say today…
  - is debatable
  - is not good advice for doing novel ML research
- Key ideas
  1. Diagnostics for debugging learning algorithms
  2. Error analyses and ablative analysis
  3. How to get started on a ML problem
     - Premature (statistical) optimization

# Motivating Example: Building a Spam Classifier

```
From: cheapsales@buystufffromme.com
To: ang@cs.stanford.edu
Subject: Buy now!

Deal of the week! Buy now!
Rolex w4tchs - $100
Med1cine (any kind) - $50
Also low cost M0rgages
available.
```

spam (1)

```
From: Alfred Ng
To: ang@cs.stanford.edu
Subject: Christmas dates?

Hey Andrew,
Was talking to Mom about plans
for Xmas. When do you get off
work. Meet Dec 22?
Alf
```

non-spam (0)

# Debugging Learning Algorithms

- Supervised learning
  - $x$ = features of email
    - carefully choose 100 words indicative of spam/not spam
    - in practice, take most frequently occurring d words (10k-50k) in training set rather than manually pick 100 words
  - $y$ = spam (1) or not spam (0)
- Learning algorithm
  - Bayesian logistic regression, implemented with gradient descent

$$\max_{\theta} \sum_{i=1}^{n} \log p(y^{(i)}|x^{(i)}, \theta) - \lambda||\theta||^2$$

  - 20% test error, which is unacceptably high
- What should you do next?

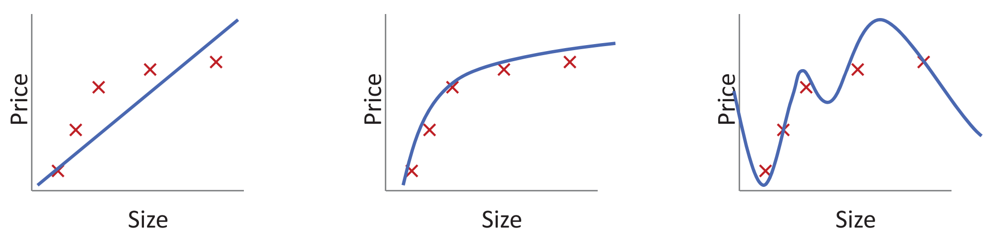
# Fixing Learning Algorithms

- Common approach: try improving algorithm in different ways…

# Diagnosing Learning Algorithms

- Better approach
  - Run diagnostic to figure out problem
  - Fix problem
- Diagnostic
  - Defn: test that you can run to gain insight what is/is not working with learning algorithm, and gain guidance as to how best to improve its performance
  - Diagnostics can take time to implement, but doing so can be a very good use of your time
- Bayesian logistic regression's test error is 20% (unacceptably high)
- Is it a bias problem or a variance problem?

# Review: Bias vs Variance




| $\theta_0 + \theta_1 x$ | $\theta_0 + \theta_1 x + \theta_2 x^2$ | $\theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3 + \theta_4 x^4$ |
|---|---|---|
| underfitting (high bias) | correct fit | overfitting (high variance) |

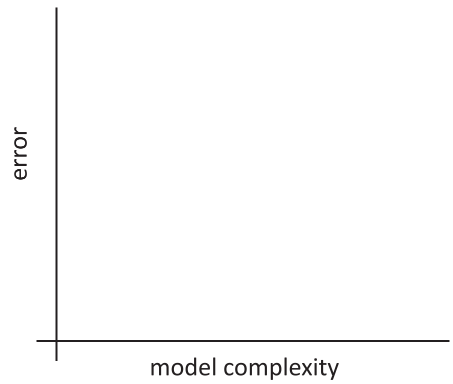
structural error
hypothesis space cannot model true relationship
$\Rightarrow$ more data does not help
$\Rightarrow$ need larger $\mathcal{H}$

**balance** $\Leftrightarrow$

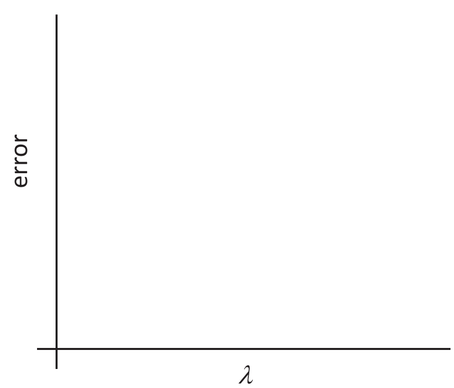
estimation (approximation) error
hypothesis space can model true relationship BUT hard to identify correct model due to large $|\mathcal{H}|$, small $n$, or noise
$\Rightarrow$ reduce $\mathcal{H}$
$\Rightarrow$ add more data

Based on slide by Eric Eaton [example by Andrew Ng]

# Bias vs Variance: Model Complexity

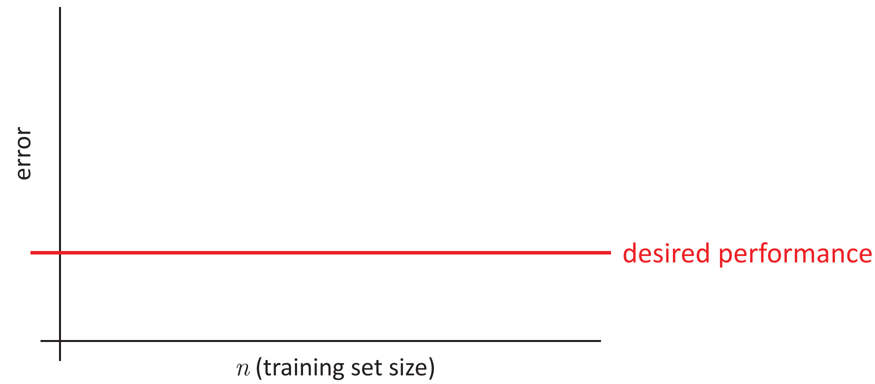



# Bias vs Variance: Regularization



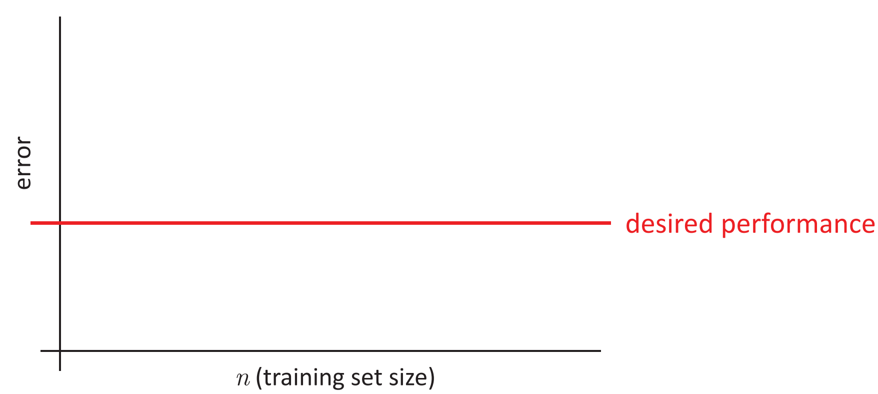
# Learning Curves

## Typical learning curve for high bias




# Learning Curves

## Typical learning curve for high variance



# Diagnostics Tell You What to Try Next

Spam classification through Bayesian logistic regression, implemented with gradient descent

| | Fixes high bias or high variance? |
|---|---|
| Try getting more training examples | |
| Try smaller set of features | |
| Try larger set of features | |
| Try changing features (email header vs email body features) | |
| Try decreasing $\lambda$ | |
| Try increasing $\lambda$ | |

# More on Diagnostics

- Quite often, you will need to come up with your own diagnostics to figure out what is happening in an algorithm
- Even if learning algorithm is worked well, you might also run diagnostics to make sure you understand what is going on. This is useful for
  - **Understanding your application problem**
    - If you are working on one important ML application for months/years, it is very valuable for you personally to get an intuitive understanding of what works and what does not work in your problem.
  - **Writing research papers**
    - Diagnostics and error analysis help convey insight about the problem, and justify your research claims.
      - i.e. Rather than saying "Here is an algorithm that works", it is more interesting to say "Here is an algorithm that works because of component X, and here is my justification."

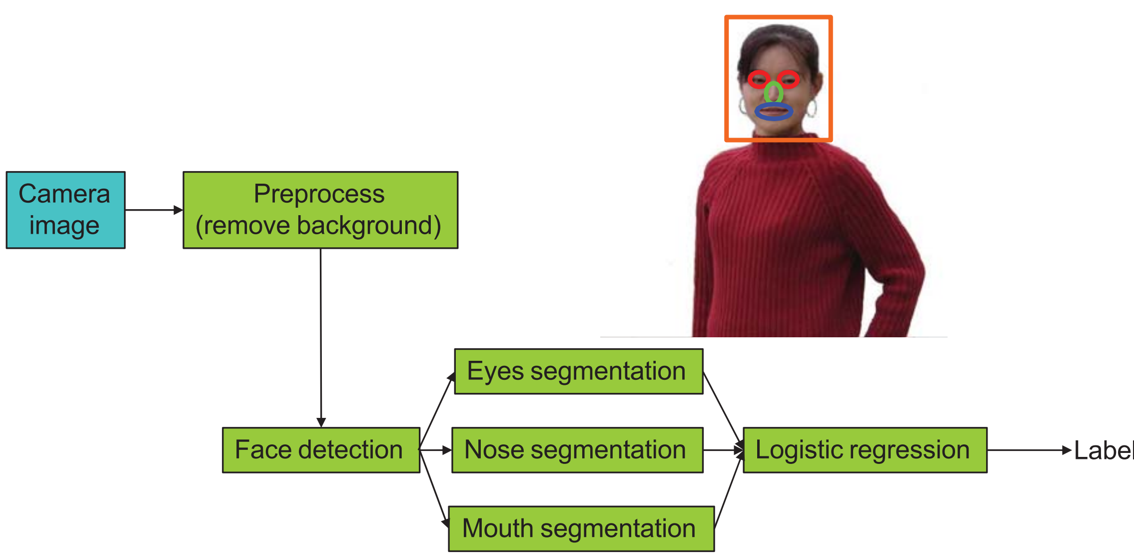
# Error Analysis

- Try to understand your sources of error -- good machine learning practice!
- Simple approach
  - Manually examine the examples (in cross validation set) that your algorithm made errors on
  - See if you spot any systematic trend in what type of examples it is making errors on
- Example
  - 500 example in CV set
  - Algorithm misclassifies 100 emails
  - Manually examine 100 errors, and categorize them based on
    - what type of email it is
      - pharma [12], replica/fake [4], steal passwords [53], other [31]
    - what cues (features) you think would have helped the algorithm classify them correctly
      - misspellings [5], unusual punctuation [32], unusual email routing [16], …

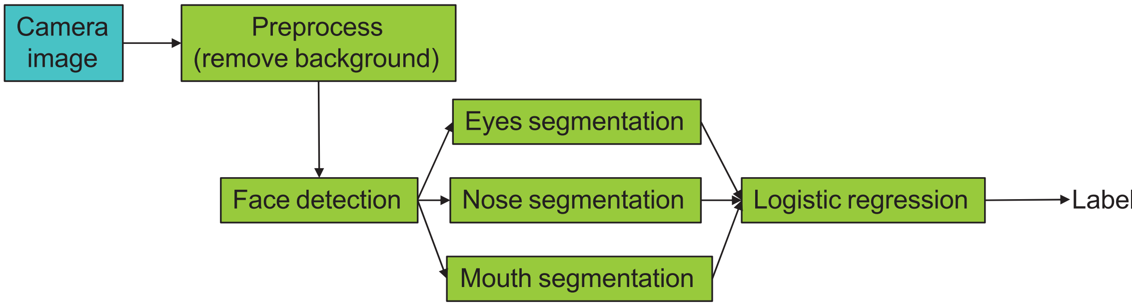
# Error Analysis

Many applications combine different learning components into a "pipeline"

- e.g. face recognition from images [contrived example]



# Error Analysis




- How much error is attributable to each of the components?
- Plug-in ground truth for (output of) each component and see how error changes
- **Conclusion**:

| component | accuracy |
|---|---|
| overall system | 85.0% |
| preprocess (remove bkgd) | 85.1% |
| face detection | 91.0% |
| eyes segmentation | 95.0% |
| nose segmentation | 96.0% |
| mouth segmentation | 97.0% |
| logistic regression | 100% |

# Ablative Analysis

- **Error analysis** tries to explain difference between current performance and perfect performance
- **Ablative analysis** tries to explain difference between current performance and some baseline (much poorer) performance

- Example: Suppose you have built a good anti-spam classifier by adding lots of clever features to logistic regression
  - spelling correction
  - sender host features
  - email header features
  - email text parser features
  - Javascript parser
  - features from embedded images
- How much did each of these components really help?

# Ablative Analysis

- Simple logistic regression without any clever features gets 94% performance
  - Just what accounts for improvement from 94% to 99.9%?
- Ablative analysis: remove components from your system one at a time to see how it breaks (remove component X, obtain accuracy Y)

| component | accuracy | |
|---|---|---|
| overall system | 99.9% | |
| spelling correction | 99.0% | |
| sender host features | 98.9% | |
| email header features | 98.9% | |
| email text parser features | 95.0% | |
| Javascript parser | 94.5% | |
| features from images | 94.0% | [baseline] |

- **Conclusion**:

# Getting Started on a Learning Problem

## Approach #1: **Careful Design**

- Spend a long time designing exactly the right features, collecting the right dataset, and designing the right algorithmic architecture
- Implement it, hope it works

### Benefits

- Nicer, perhaps more scalable algorithms
- May come up with new, elegant learning algorithms and contribute to basic research in machine learning

## Approach #2: **Build-and-Fix**

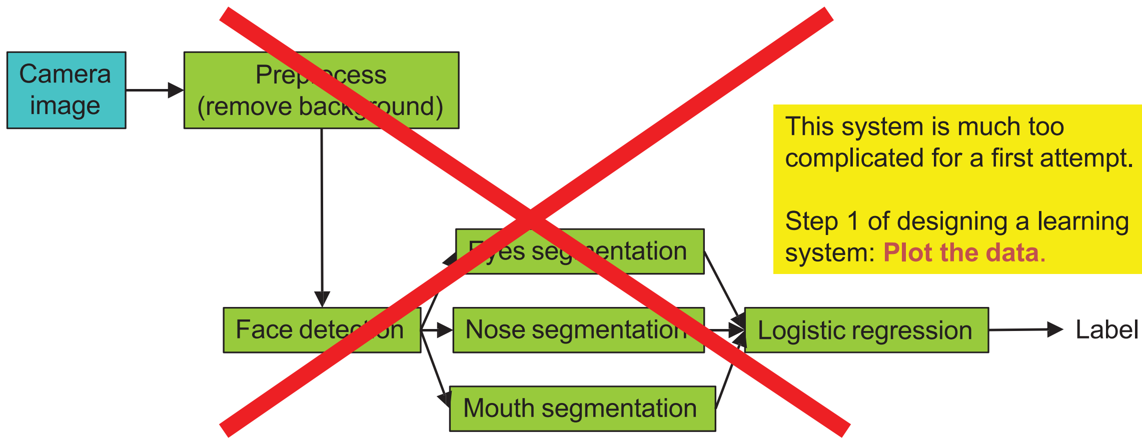
- Implement something quick-and-dirty
- Run error analyses and diagnostics to see what is wrong with it, and fix errors

### Benefits

- Will often get your application problem working more quickly, so faster time-to-market

# Premature Statistical Optimization

- Very often, it is not clear what parts of system are easy or difficult to build, and which parts you need to spend lots of time focusing on, e.g.
- The only way to find out what needs work is to implement something quickly and find out what parts break
  - But this may be bad advice if your goal is to come up with new ML algorithms



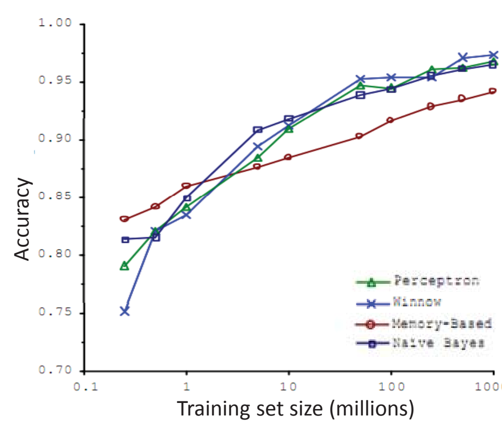

# Data for Machine Learning

Task: Classify between confusable words.

{to, two, too}

{then, than}

For breakfast I ate _____ eggs.




"It's not who has the best algorithm that wins.
It's who has the most data."

-- Banko and Brill 2001

# Large Data Rationale

- Assume feature $x$ has sufficient information to predict $y$ accurately
  - Example: For breakfast I ate {to, two, too} eggs
  - Counterexample: Predict housing price from only size (feet$^2$) and no other features
- Useful test: Given input $x$, can human expert confidently predict $y$?

- Why large data?
  - Use learning algorithm with many parameters (e.g. logistic regression/linear regression with many features)
    - low bias algorithms, so $J_{\text{train}}(\boldsymbol{\theta})$ will be small
  - Use very large training set (unlikely to overfit)
    - low variance, so $J_{\text{train}}(\boldsymbol{\theta}) \approx J_{\text{test}}(\boldsymbol{\theta})$
    - combined with above, $J_{\text{test}}(\boldsymbol{\theta})$ will be small

# Summary

- Time spent coming up with diagnostics for learning algorithms is time well-spent
  - It is often up to your own ingenuity to come up with right diagnostics

- Error analyses and ablative analyses also give insight into problem

- Two approaches to applying learning algorithms
  - Design very carefully, then implement
    - Risk of premature (statistical) optimization
  - Build a quick-and-dirty prototype, diagnose, and fix