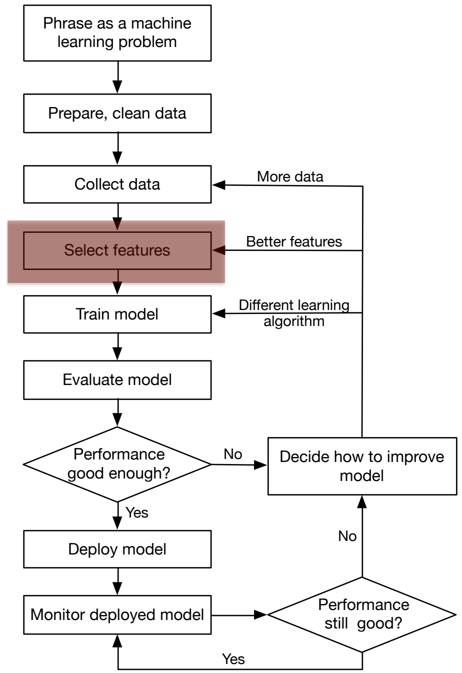
IRDS: Choosing Features

Charles Sutton
University of Edinburgh

Why features?

- Every learning algorithm somehow assumes:
  - "similar input vectors have similar labels"
- **Features** determine what is similar
- For practical ML, two best ways to improve performance
  - Get more training data
  - Come up with better features
- Feature engineering is a way to introduce prior knowledge about the problem
- (For ML research, advice would be different!)



General Principles

- Feature engineering is **iterative** (and messy)
  - Come up with a new feature
  - Try it on a validation set, measure error
  - Repeat
- Use an **ablative** design (NB gains don't always accumulate nicely)

Feature Set A	70%
Feature Set A+B	75%
Feature Set A+B+C	75.2%

- Use **error analysis**
  - Look at the most embarrassing mistakes
  - What features might help with those
- Training set versus validation set versus test set
  - Once you have tuned features on a data set, you can't use the error to predict future performance
- Flexibility versus overfitting

1-of-K ("one hot") encoding

Age	Fav. Colour	Label
26		+
57		-
34		+

Age	Fav. Colour	Label
26	0	+
57	1	-
34	2	+

This can cause problems.
(Is yellow really twice as related to label as blue?)

Age	Red?	Yellow?	Blue?	Label
26	1	0	0	+
57	0	0	1	-
34	0	1	0	+

Convert to K binary features
("1-of-K" or "one hot" encoding)

For which algorithms will this matter?

Normalization (Whitening)

For continuous features, can be best to have zero mean and unit variance

Feature index k

Sample mean, feature k

$$x_k \mapsto \frac{x_k - \hat{\mu}_k}{\hat{\sigma}_k}$$

Sample standard deviation

or in vector notation

Entire training example

$$\mathbf{x} \mapsto \Sigma^{-1/2}(\mathbf{x} - \hat{\mu})$$

Sample covariance matrix (or: just diagonal entries)

For which algorithms will this matter?

Binning (Discretization)

We've mentioned nonlinear feature transforms

$$x_k \mapsto x_k^2$$

What if you do not expect a simple functional form is appropriate?

One possibility: Convert to M binary variables

$$x_k \mapsto \begin{pmatrix} \mathbb{I}\{x_k \in (-\infty, \tau_1]\} \\ \mathbb{I}\{x_k \in (-\tau_1, \tau_2]\} \\ \vdots \\ \mathbb{I}\{x_k \in (\tau_{M-1}, \infty)\} \end{pmatrix}$$

Feature Conjunctions

If features binary, natural interpretation:

- each feature is a proposition, e.g. "does document *i* contain the word 'geranium'"

Then, why not combine different features?, e.g.,

- "does document *i* contain both the word 'geranium' and 'magnolia'"

This is a product of feature values, i.e.,

$$\begin{pmatrix} x_j \\ x_k \end{pmatrix} \mapsto \begin{pmatrix} x_j \\ x_k \\ x_j x_k \end{pmatrix}$$

In principle we could do this for all pairs (or higher). Might reduce this using feature selection.

Sequences of Predictions

Examples:

- Predict part of speech for each word in a sentence
- Predict number of web requests for each day
- Predict for each window of an image whether it contains a face

For these, think about features

- At different "lags"
- At different levels of granularity

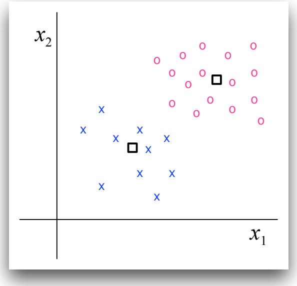
Such as:

- Identity of word at location *t, t-1, t-2 …*
- Average number of searches in past week, month, year
- Feature statistics from surrounding regions
- True (or predicted) value from previous time step

Vector Quantization

Use the output of some other algorithm to get features:

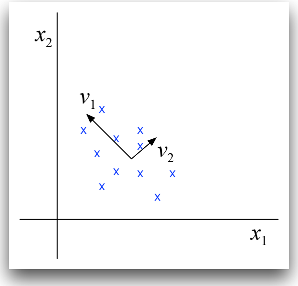
- Run k-means clustering
- For each data point, add a feature that gives the index of the closest cluster centroid.
- (Could use one of k encoding.)
- This is a generalisation of the 1-D binning idea from previous slide



Dimensionality Reduction

Principal Components Analysis returns a linear map

$$\begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_M \end{pmatrix} \mapsto \begin{pmatrix} z_1 \\ \vdots \\ z_P \end{pmatrix} \qquad P << M$$



Use **z** as features instead of (or in addition to?) **x**

Could use fancier techniques, e.g.,
- manifold learning
- topic modelling
- deep neural networks
  (activations of hidden layer)

Model Combination

Suppose you want to improve on existing systems.
Just add their output as a feature to your classifier!

If they provide a confidence, e.g., a probability
could use predicted log probability as feature

Examples:
- Machine translation
- Netflix prize

Simple Transfer Learning

Common: Need to solve "lots of little prediction problems"
- Email spam filter for each person
- Fraud detection of personal credit card accounts

Compare *domain adaptation, transfer learning, multitask learning*

Different prediction tasks not identical

Features can have different meanings across tasks, e.g.,
- "Viagra" commonly included in spam emails
- But a GP might often see it in regular emails

But similar and only a small amount of data for each

Simple Transfer Learning

Common: Need to solve “lots of little prediction problems”

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Compare *domain adaptation, transfer learning, multitask learning*

Trick: Both “general” and “specific” features:

- USER872324601_CONTAINS:Viagra
  - binary feature, 1 only if email contains “Viagra” and inbox from specified user
- CONTAINS:Viagra
  - binary feature, 1 if email contains “Viagra”

Example in research literature:

Daumé, *Frustratingly Easy Domain Adaptation.* ACL 2007

Feature Selection

Sometimes too many features bad.
Start with “full set” of features, prune less useful ones.

- Filters: Rank features by some “relevance” measure, e.g., mutual information, correlation with output. Choose top *K.* (Also called ranking, screening).
- Wrapper methods: Search through space of subsets of full feature set, to maximise performance on validation set. Many different strategies (forward versus backward)
- Wrapper as filter : Use a wrapper method on a linear classifier to find a good set of features, then train a (more computationally expensive) nonlinear one
- Lasso (l1 regularization) : Classification/regression and feature selection simultaneously