



SPARKBEYOND

# PRIOR ON MODEL SPACE

What makes a model simple?



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# Outline

Why are simple models desirable

Traditional approaches for simplicity

Alternative approaches



# Why Simple models?

PAC model

No Free Lunch

Better generalization

In Reality

Transfer learning and non stationary distributions

Robust against correlated samples, etc.



Leslie Valiant, 1984



# Why Simple Models? Cont.

Understandable

Trustworthy

Explainable (also for Regulatory reasons)

Understandable models are ultimately more accurate





# Traditional complexity control

Bias / Variance tradeoff  $\rightarrow$  We must limit our search space

Shrink the hypothesis space:

- limit boosting iterations

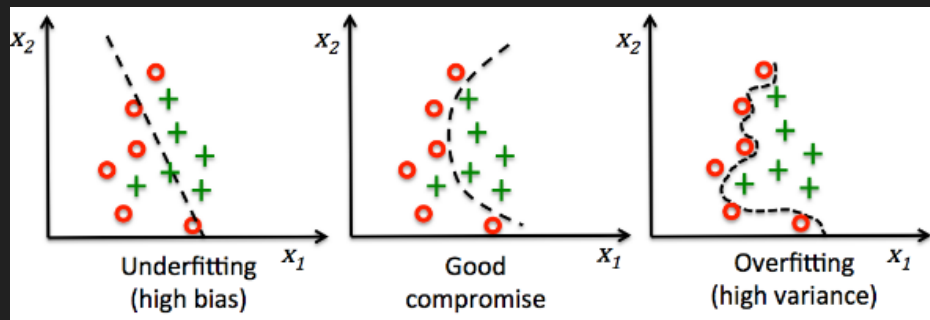
- tree size

- min sample in leaf

- number of hidden nodes

- impose sparsity constraint

- ...





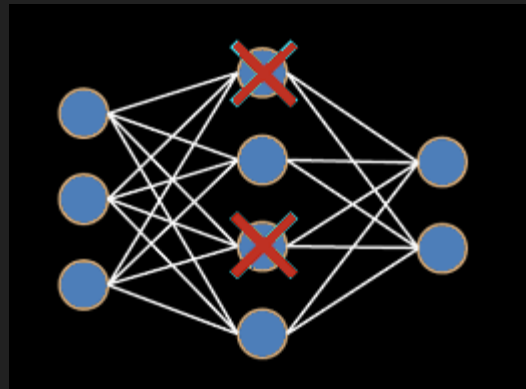
Traditional complexity control cont.

Penalize “less favourable” models:

Lasso / ridge regularization

Bagging / Boot strap sampling

Drop out





# Which is more likely?

Coefficients from two feed forward ReLu NN  
single-output single hidden layer

NETWORK A

1.787  
1.771  
1.735  
1.937  
1.445  
1.601  
1.773  
2.017  
1.418  
1.888  
1.399  
1.733  
2.031  
1.723  
1.801  
1.598  
1.666  
1.484

NETWORK B

-0.590  
0.000  
0.000  
0.806  
0.000  
0.000  
0.092  
0.000  
0.000  
0.000  
0.000  
0.000  
0.000  
-0.932  
0.525  
0.000  
0.097  
0.000



# Which feature is a more likely?

Both have  $\mathbb{R}^2 = 0.1$

`Math.ulp(x)` - The positive distance between this floating-point value and the double value next larger in magnitude

vs.

`Math.log(x)` - Natural logarithm





Which is a more likely feature? #2

The distance to the nearest railway station?

vs.

$\arctan(\text{latitude} * \text{longitude})$



# Everyone is a domain expert!

We are experts in the world we live in.

Currently, humans have a much better prior than machines.

Many ideas repeat themselves across domains.

For example, you don't have to be a rocket scientist to be familiar with second derivatives.



# Transfer Learning to the rescue

We can and must learn from previous problems

How can a child learn to identify a Ring Tailed Lemur from a single photo?





# Becoming common

Pre-Trained Neural networks

Pre-Trained embeddings

A lot of work on Images and Text

Much less research on other data:

- TimeNet - RNN for embedding time series data

- Most real-life problems tend to have a more complicated shape



# A different approach

Use already codified human knowledge

Explicitly look for patterns similar to things you have seen before

Extraordinary claims require extraordinary evidence



# At SparkBeyond

Find the best hypotheses, using simple compositions of tried and true building blocks

The building block may require a lot of code to implement. Yet, will be useful across domains

Incorporate pre-trained embeddings

Use external knowledge

Prioritize simple hypotheses

Always meta-learn how to learn

## *Shops near **recreational parks** are more successful*

- *Domain expert can review such a finding*
  - *True phenomenon*
  - *Insightful and actionable*



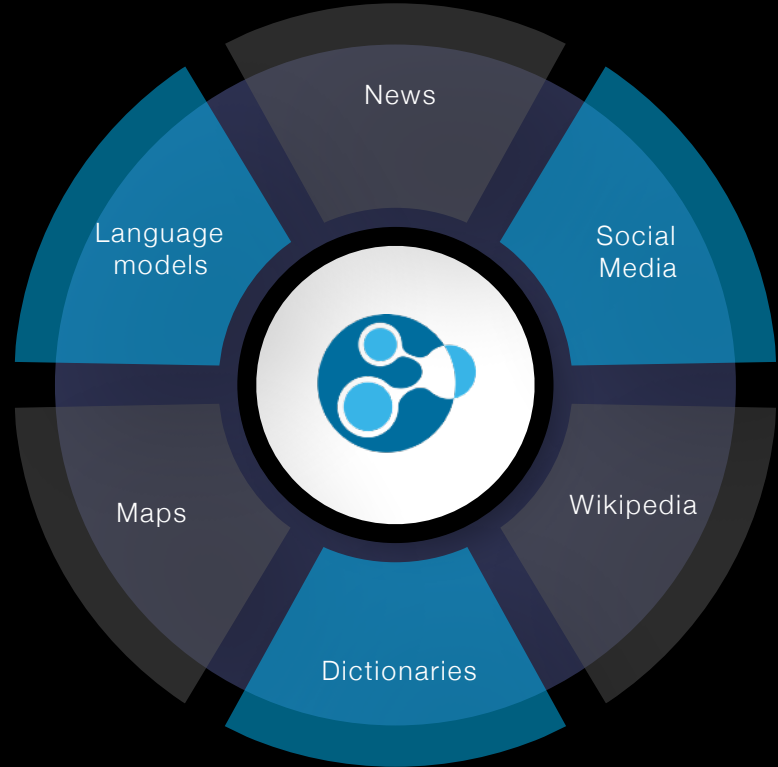
*Colorful gadgets tend to be cheaper*

*Becomes intuitive when you see concrete examples*





# EXTERNAL DATA





# Simple = compressible = common

A simple model or feature is one which we can be expressed briefly.

MDL - minimum description length is optimal compression.

Better compression leads to better model performance.

But should we be using a vanilla Turing machine for MDL?



# Benefits of a better prior

Learn with less data

More robust to change

More robust to data issues

Understandable and explainable

Actionability without a complete model



# Open questions and challenges

What is simple?

What makes an insight insightful?

What makes a feature likely to generalize?

Efficient search over insightful hypothesis space



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