IMPACT 2019
SEATTLE WASHINGTON USA

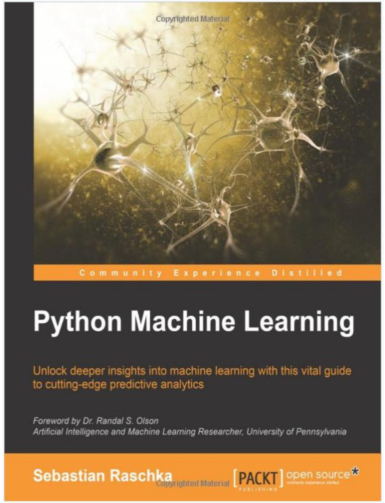
CMG imPACt 2019

Introduction to Machine Learning

Alex Gilgur, Odysseas Pentakalos
CMG imPACt 2019 International Conference
Seattle, WA February, 2019

Some Books

https://amzn.to/2PB81hB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Community Experience Distilled
Python Machine Learning
Unlock deeper insights into machine learning with this vital guide to cutting-edge predictive analytics
Foreword by Dr. Randal S. Olson
Artificial Intelligence and Machine Learning Researcher, University of Pennsylvania
Sebastian Raschka
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PACKT
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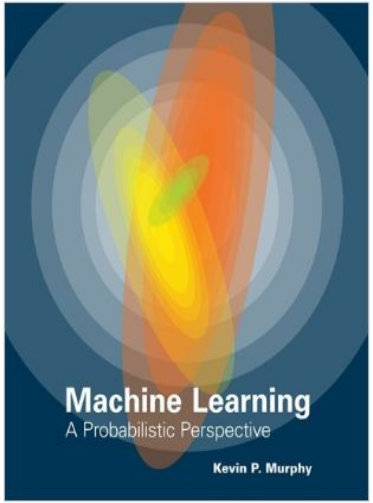
https://bit.ly/2A3t9lM



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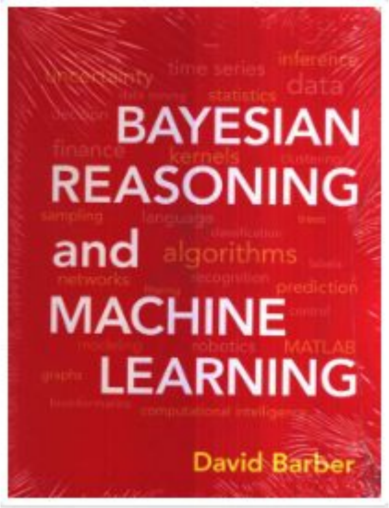

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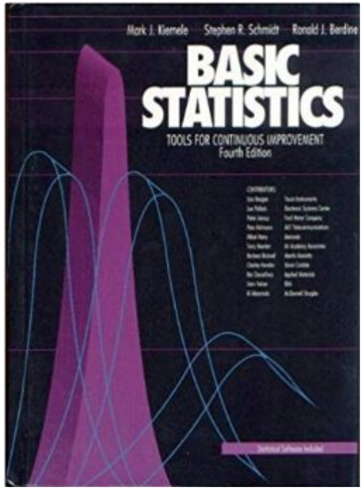


Some General Information and Ideas

- Machine Learning vs. Statistical Learning vs. Scientific Programming
- Ideal setup:
  - I7 CPU (or GPU) 16+ GB RAM
  - R v3.4.x + RStudio
  - Anaconda python 3.6+
  - Tensorflow
  - Keras or Cafe or Torch
- Non-programmer tools:
  - KNIME
  - Rattle
  - Wordij
  - Gephi
  - Tableau - if you still want to be in the driver's seat of your algorithms.
- Hypothesis Testing
- No Free Lunch Theorem
- Bias/Variance tradeoff
- Ensemble Modeling
- Bayesian Approach
- Patrick Winston's theory of Incremental Learning (vs. Locke's Tabula Rasa theory)
- "Anybody can learn to code. And everyone should give it a try"(Bill Gates on Twitter). So we will.

Flow

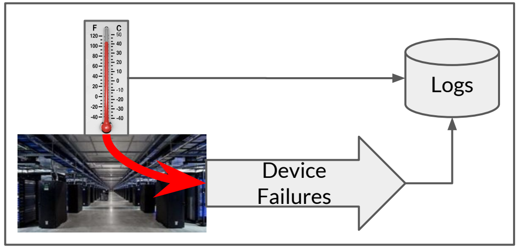
1. Device Failure Prediction:
    a. Regression and Logistic Regression
    b. Line fit and significance of parameters

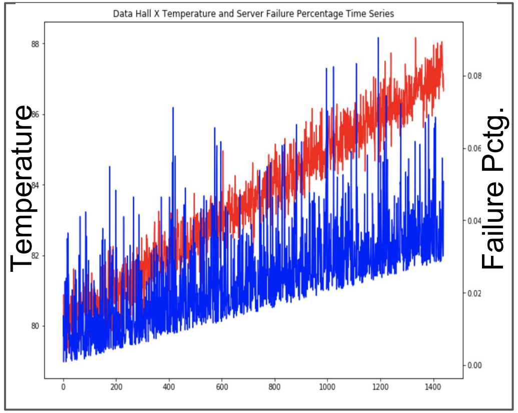
2. Queue Assignment based on Response Times:
    a. Distributions
    b. Clustering
    c. Classification
    d. Accuracy

3. ML Workflow:
    a. Data Engineering
    b. Split
    c. Train
    d. Test

4. Model Quality

Example 1: Predicting Device Failure Probability

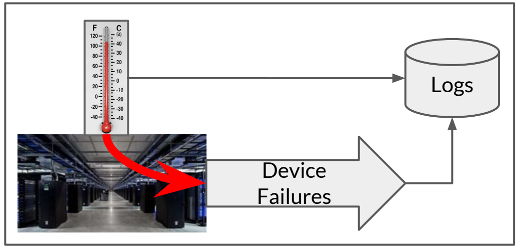




Is there a correlation between temperature and failure probability? If there is, can we use it to predict ***Pr{fail}***?

The Jupyter Notebook is here

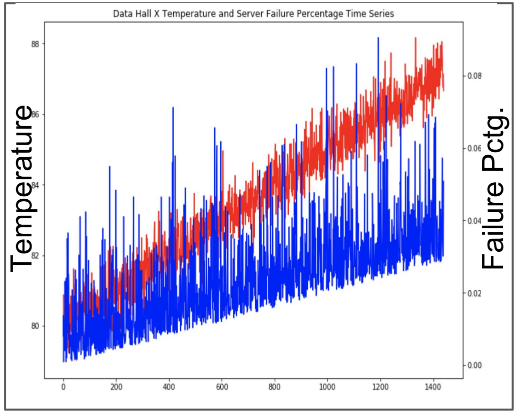
Example 1: Predicting Device Failure Probability

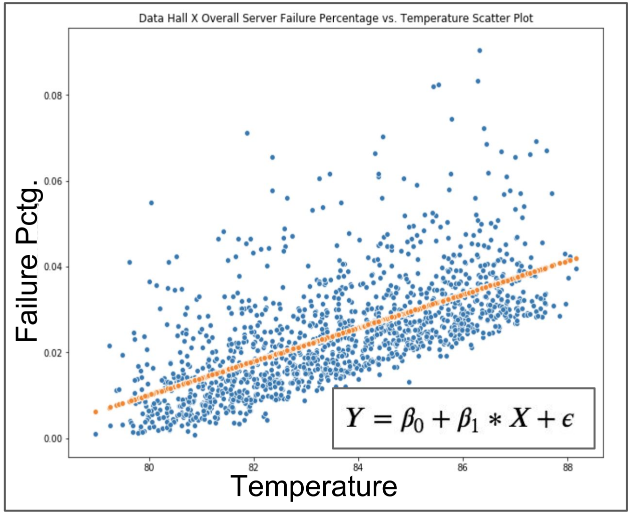


Logs

Device Failures

Is there a correlation between temperature and failure probability? If there is, can we use it to predict ***Pr{fail}***?


Data Hall X Temperature and Server Failure Percentage Time Series


Data Hall X Overall Server Failure Percentage vs. Temperature Scatter Plot

$$Y = \beta_0 + \beta_1 * X + \epsilon$$

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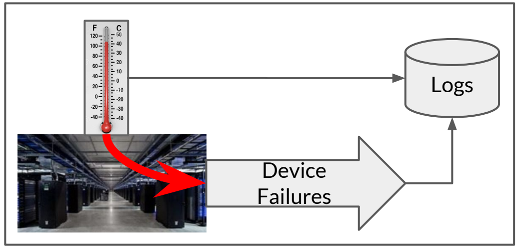

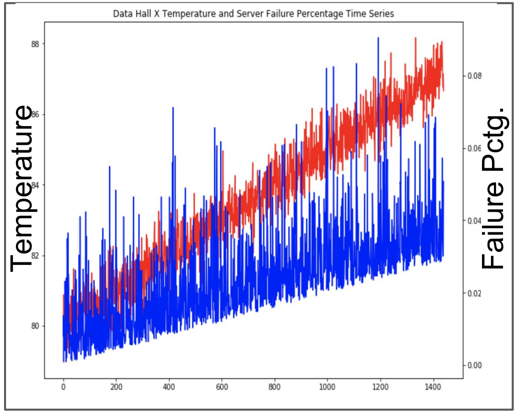

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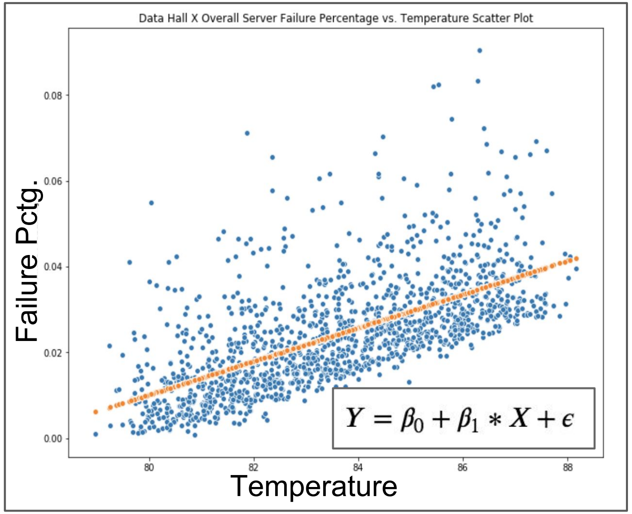

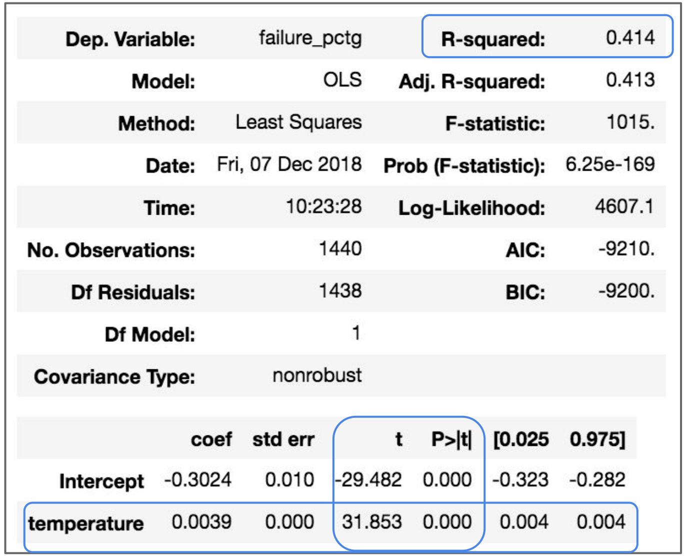

Dep. Variable:	failure_pctg	**R-squared:**	0.414
Model:	OLS	**Adj. R-squared:**	0.413
Method:	Least Squares	**F-statistic:**	1015.
Date:	Fri, 07 Dec 2018	**Prob (F-statistic):**	6.25e-169
Time:	10:23:28	**Log-Likelihood:**	4607.1
No. Observations:	1440	**AIC:**	-9210.
Df Residuals:	1438	**BIC:**	-9200.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	-0.3024	0.010	-29.482	0.000	-0.323	-0.282
temperature	0.0039	0.000	31.853	0.000	0.004	0.004

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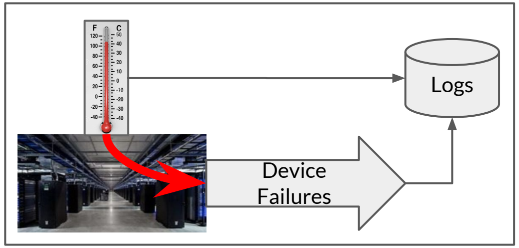

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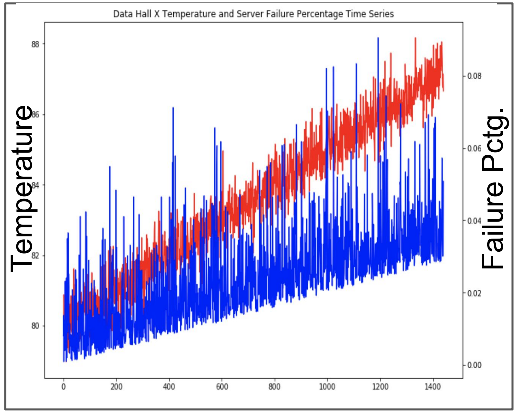
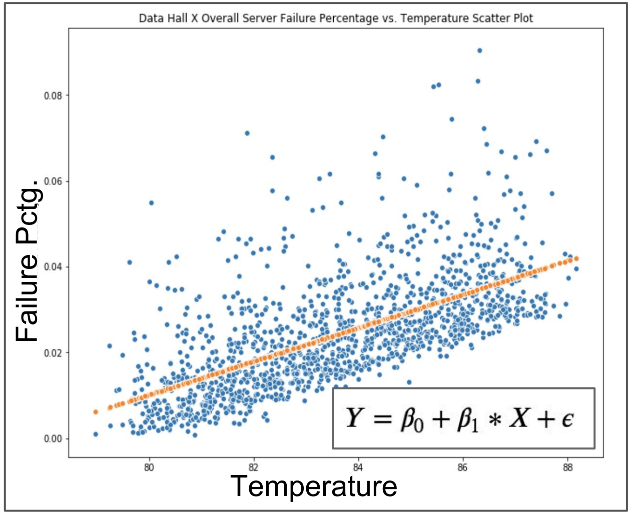
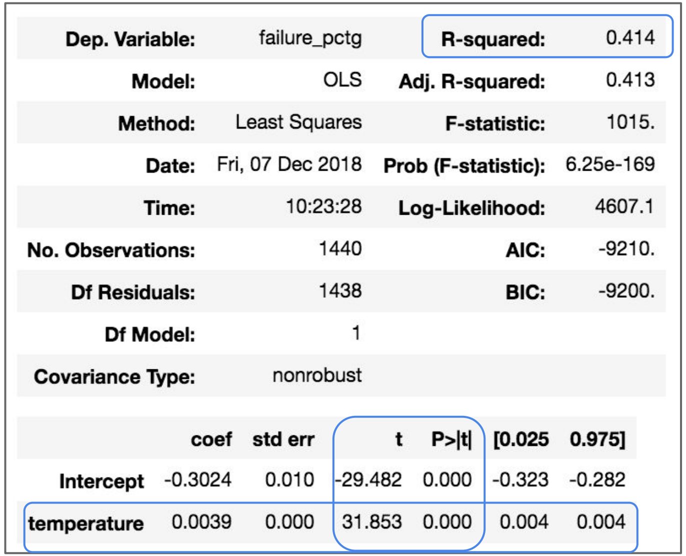




$$Y = \beta_0 + \beta_1 * X + \epsilon$$



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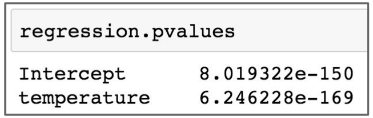
Intercept	-0.3024	0.010	-29.482	0.000	-0.323	-0.282
temperature	0.0039	0.000	31.853	0.000	0.004	0.004

$$R^2 = 41.4\%$$

$$\beta_1 = \rho_{Y\_X} * \frac{\sigma_Y}{\sigma_X}$$

$$T = \frac{\beta_1 - 0}{\frac{\sigma_{resid}}{\sqrt{N_{df}}}}$$

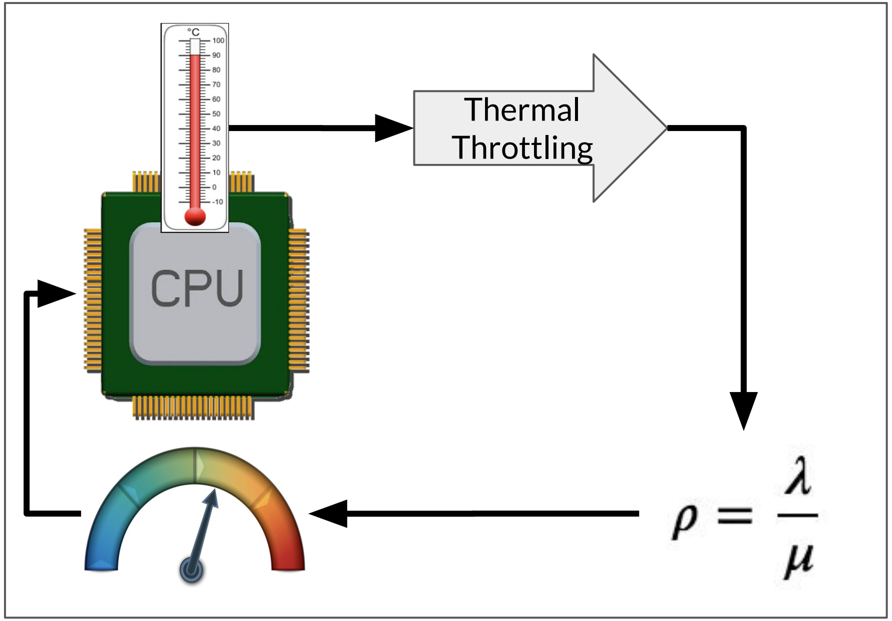


```
regression.pvalues

Intercept      8.019322e-150
temperature    6.246228e-169
```

The Jupyter Notebook is here

Example 2: Logistic Regression



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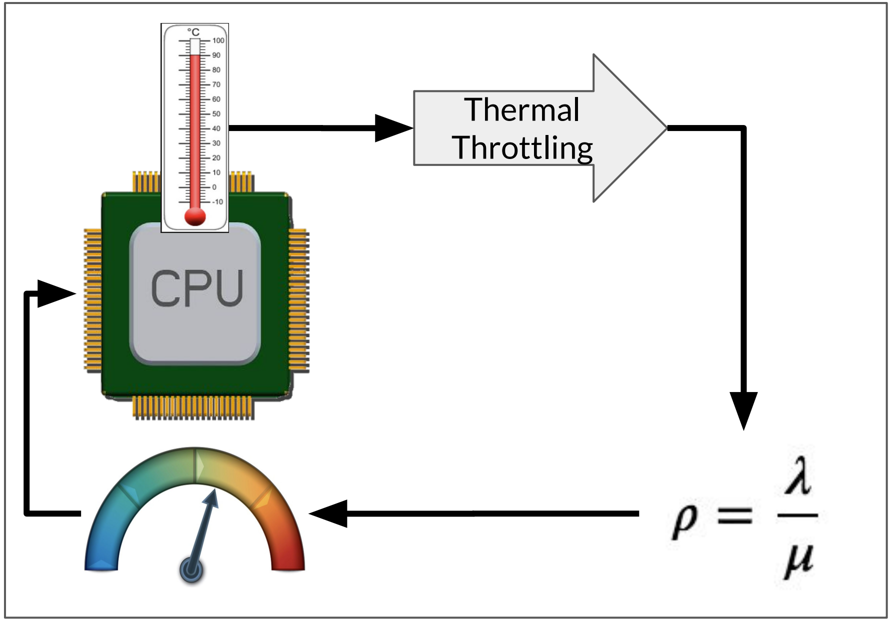
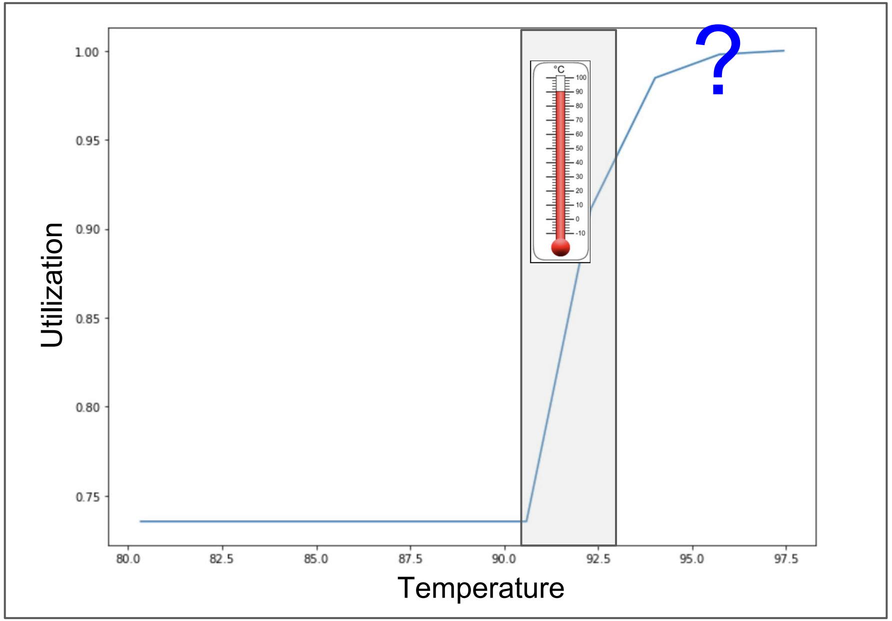


Thermal Throttling

$$\rho = \frac{\lambda}{\mu}$$



Given utilization measured between 90 and 93 degrees, how far will utilization grow due to throttling if the temperature rises to 97 degrees?

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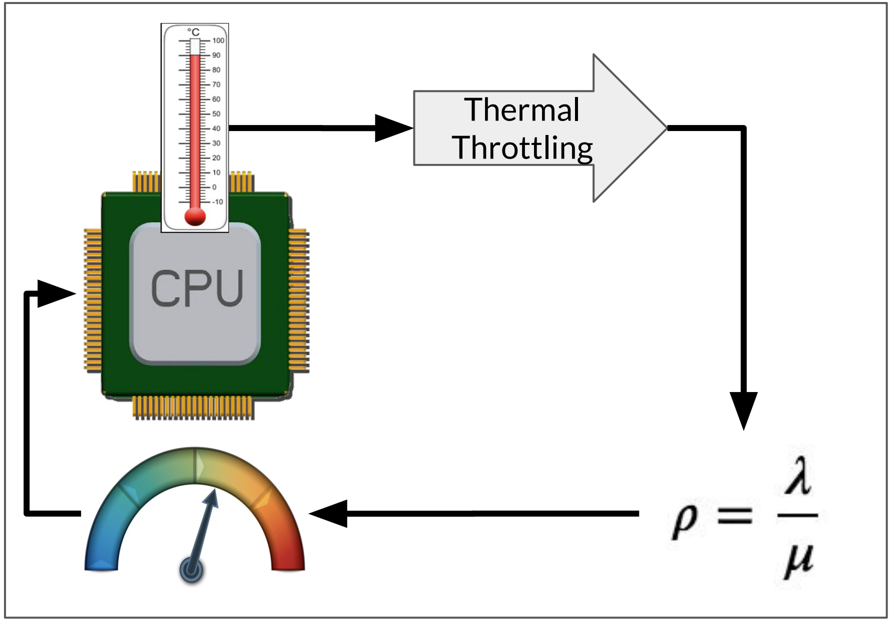

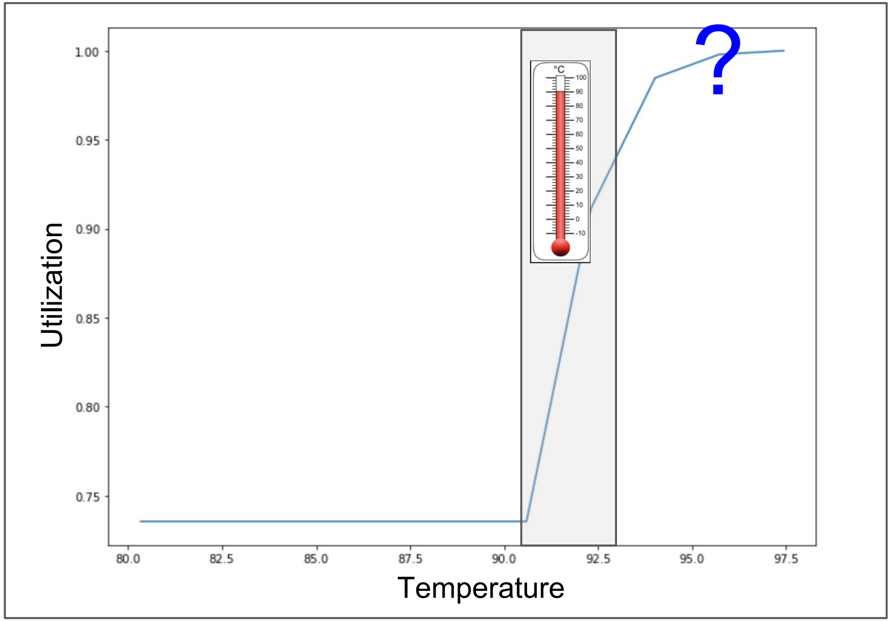

Given utilization measured between 90 and 93 degrees, how far will utilization grow due to throttling if the temperature rises to 97 degrees?

$$Y' = \ln\left[\frac{\rho}{1-\rho}\right] = \beta_0 + \beta_1 * T$$

$$\Longrightarrow$$

$$\rho = \frac{e^{\beta_0} * e^{\beta_1 * T}}{1 + e^{\beta_0} * e^{\beta_1 * T}}$$

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Example 3: Clustering

Grouping services by Response Times: services svc1-svc4 are funneling into one interface, and we want to make sure that faster services are not waiting for the slower ones.

Due to resource constraints, we cannot allocate more than 2 instances of the interface. So we need to cluster the services into two groups.

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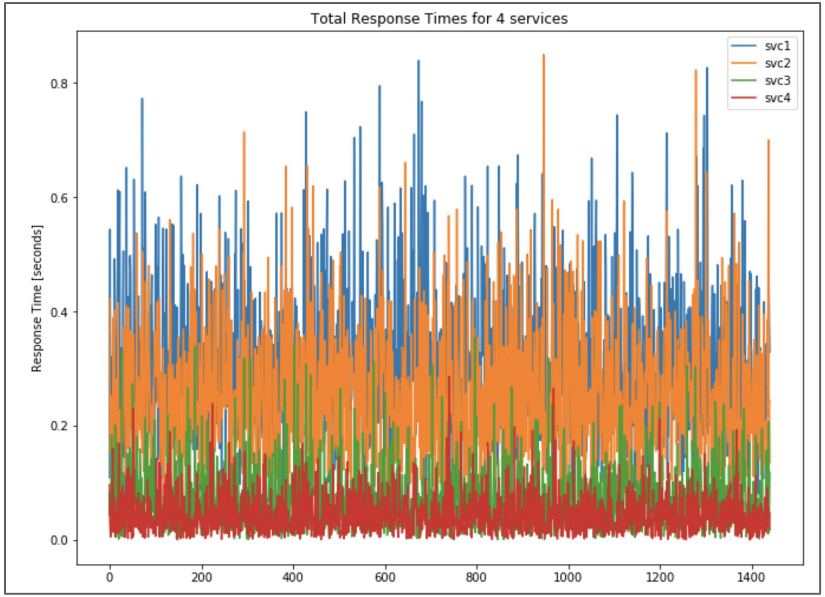

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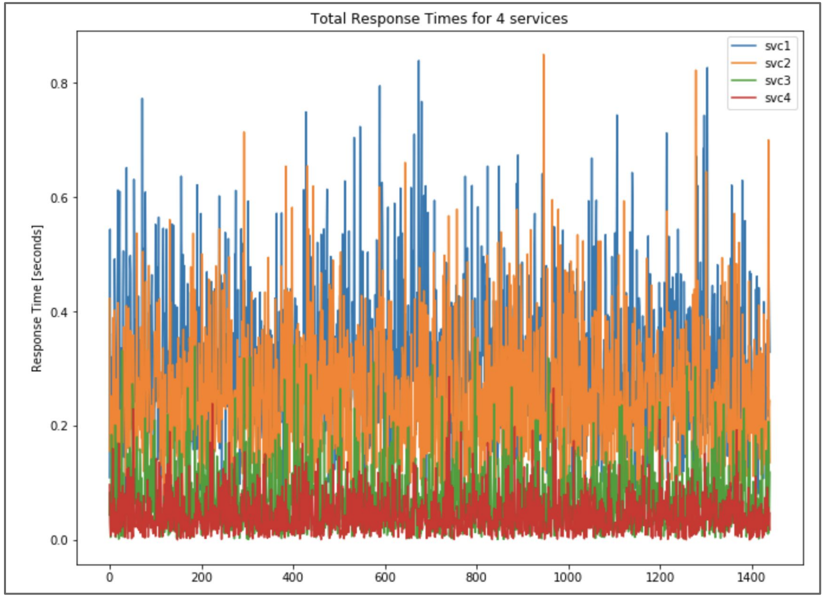

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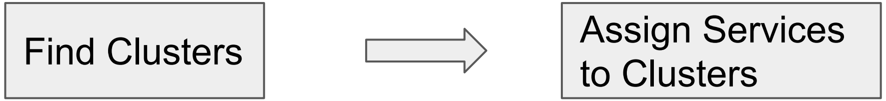

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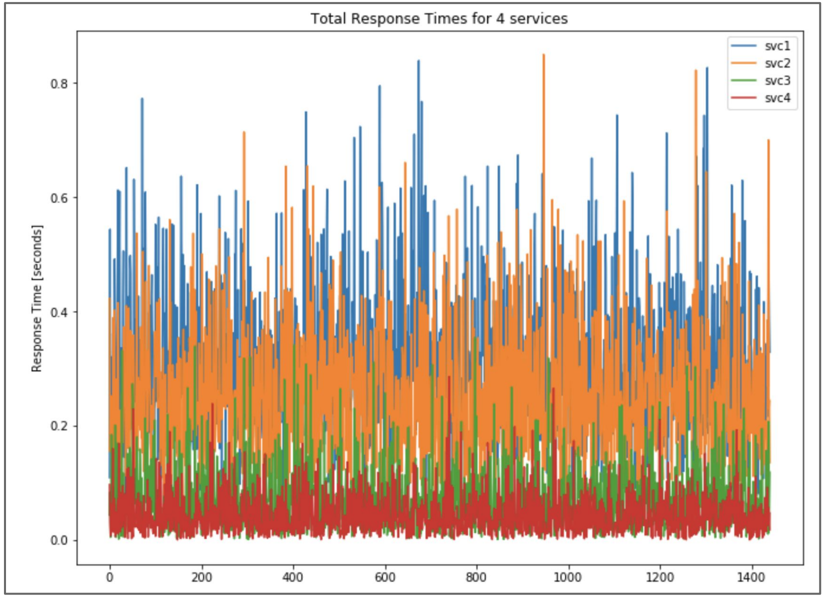

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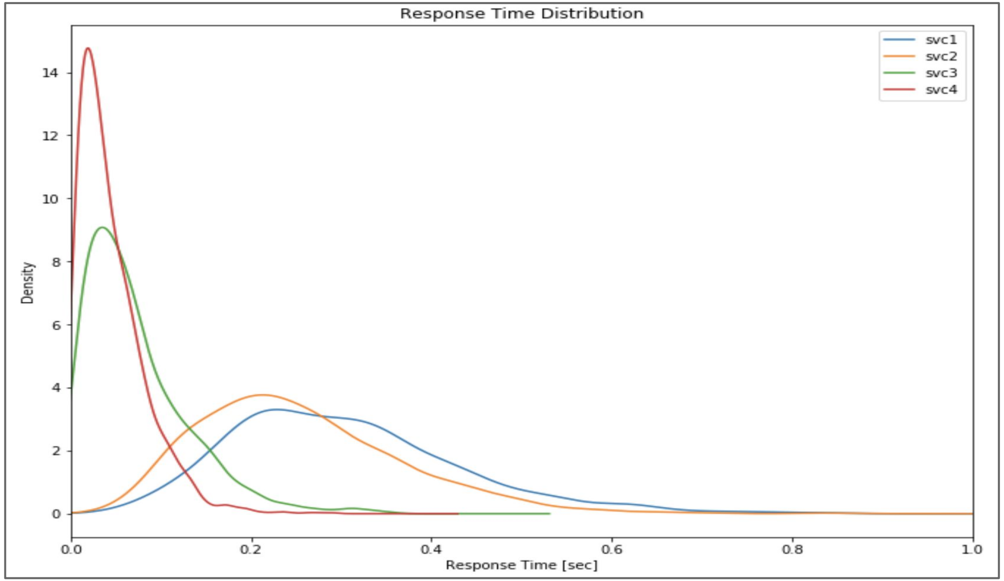

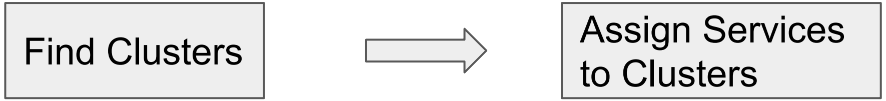

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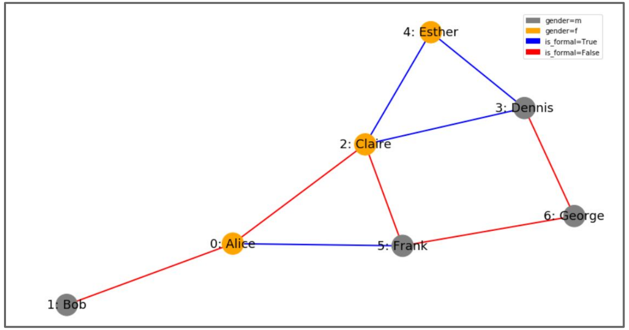
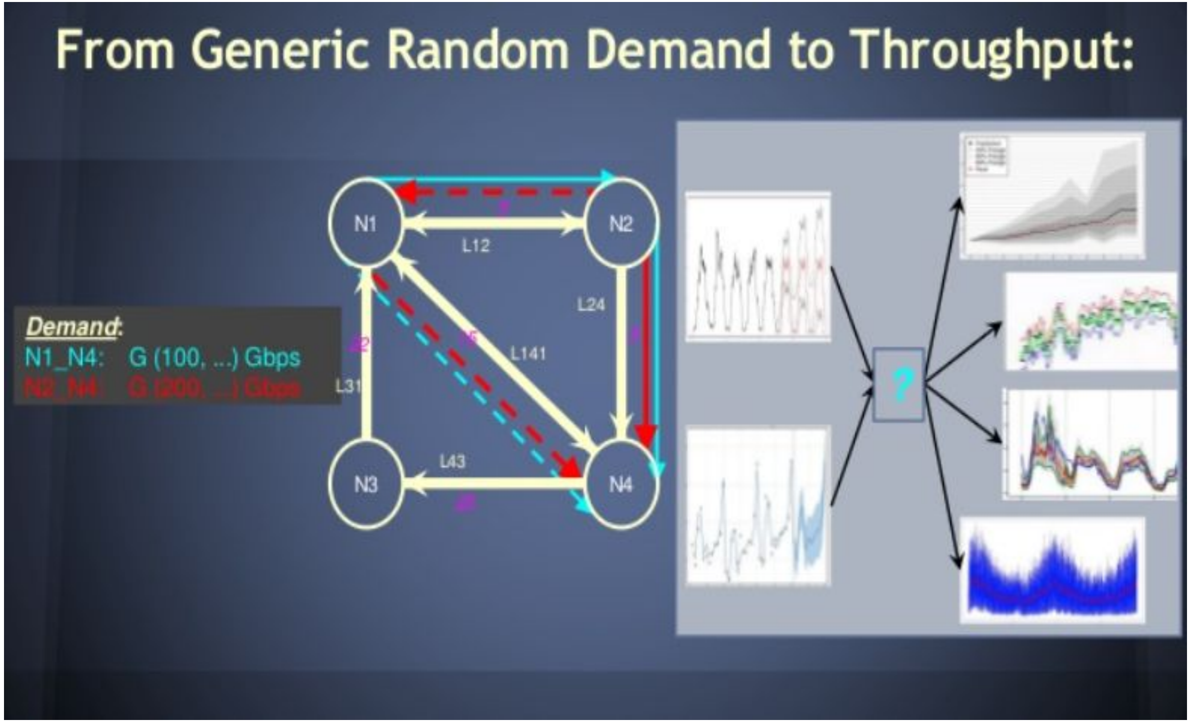
Network Analysis Introduction





From Generic Random Demand to Throughput:

***Demand*:**

N1_N4: G (100, ...) Gbps

N2_N4: G (200, ...) Gbps

A slide from a CMG'14 paper: https://bit.ly/2BO2BGc (a shameless act of self-advertisement)

Node Attributes

Degree Distribution

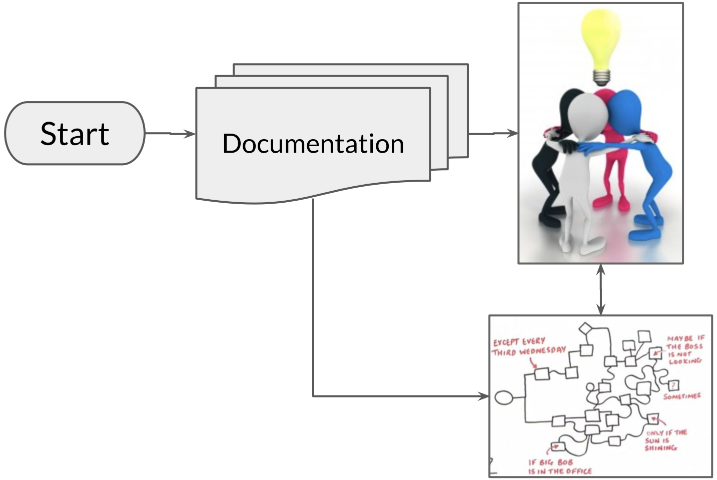
Shortest Path

Node Centrality

More on the topic is in this PDF

The Jupyter Notebook is here.

The Life of a Model: Waterfall


Start
Documentation
EXCEPT EVERY THIRD WEDNESDAY
MAYBE IF THE BOSS IS NOT LOOKING
?
SOMETIMES
ONLY IF THE SUN IS SHINING
IF BIG BOB IS IN THE OFFICE

Also see here:
https://github.com/chemodan/ml_training_for_cmg_impact/blob/master/PDF/ML%20Process%20Flow%20Fit%20Metrics%20and%20Entropy.pdf

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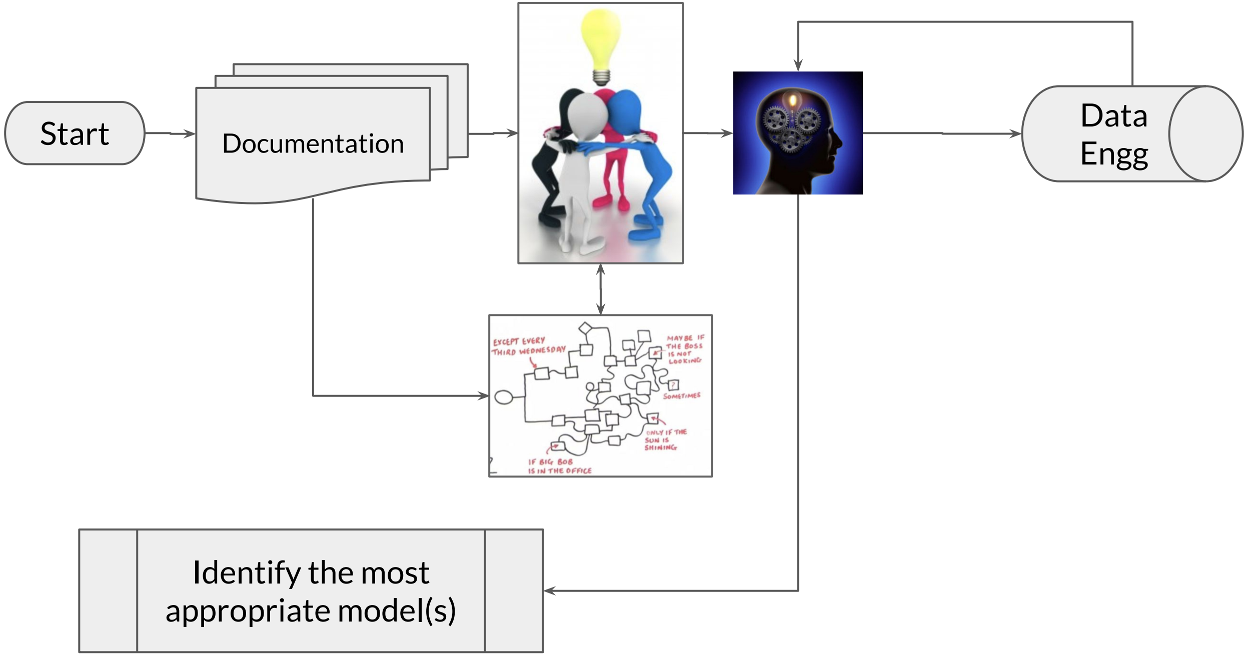

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Documentation

Data Engg

Identify the most appropriate model(s)

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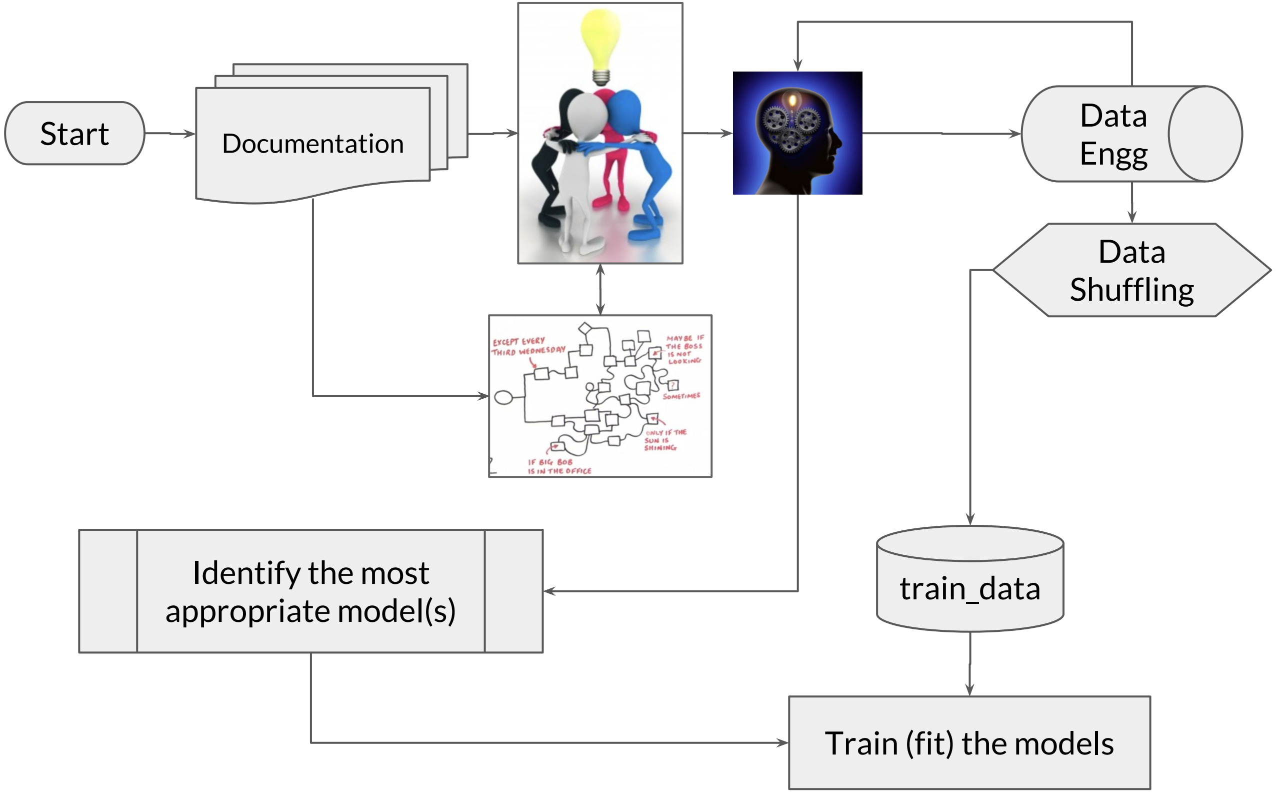

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Data Engg

Data Shuffling

train_data

Identify the most appropriate model(s)

Train (fit) the models

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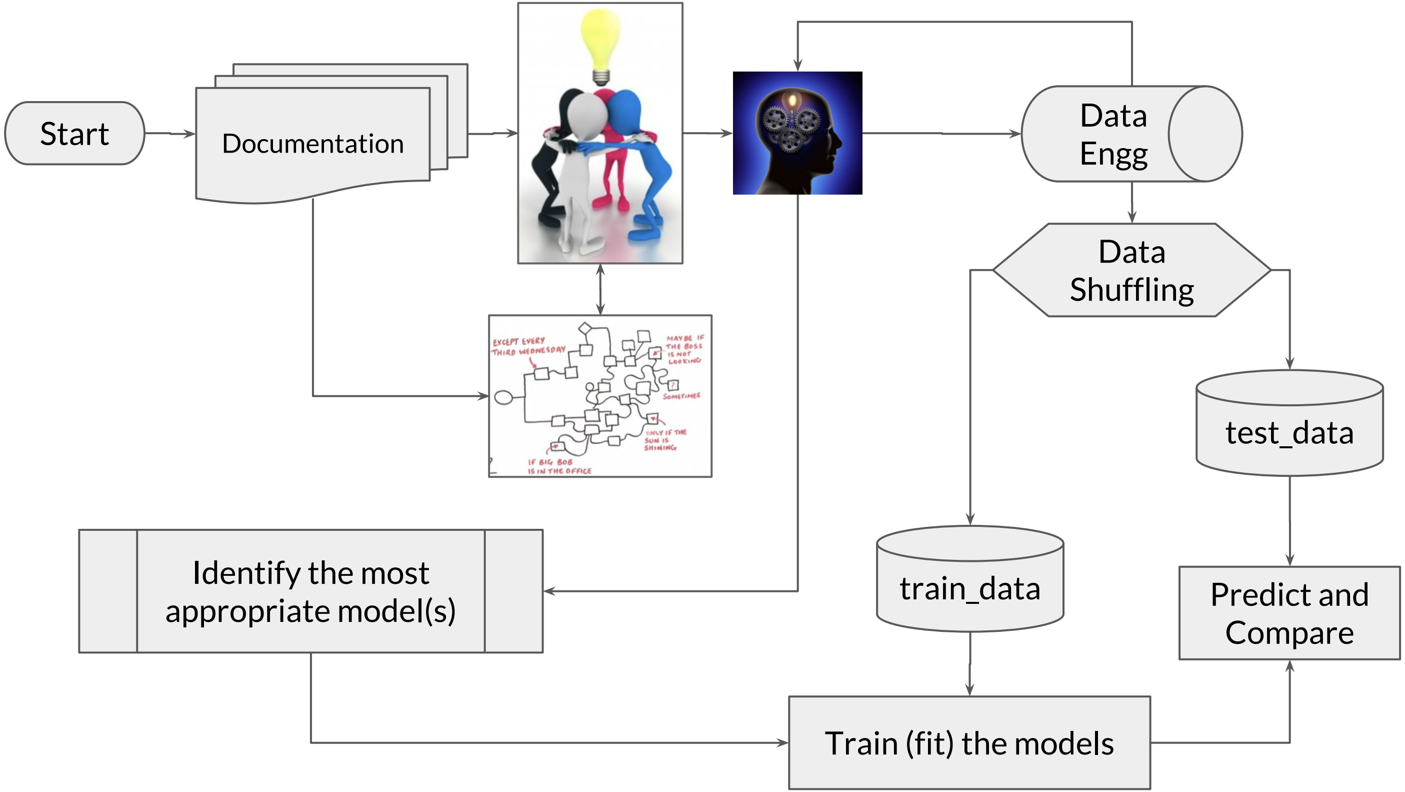
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Identify the most appropriate model(s)
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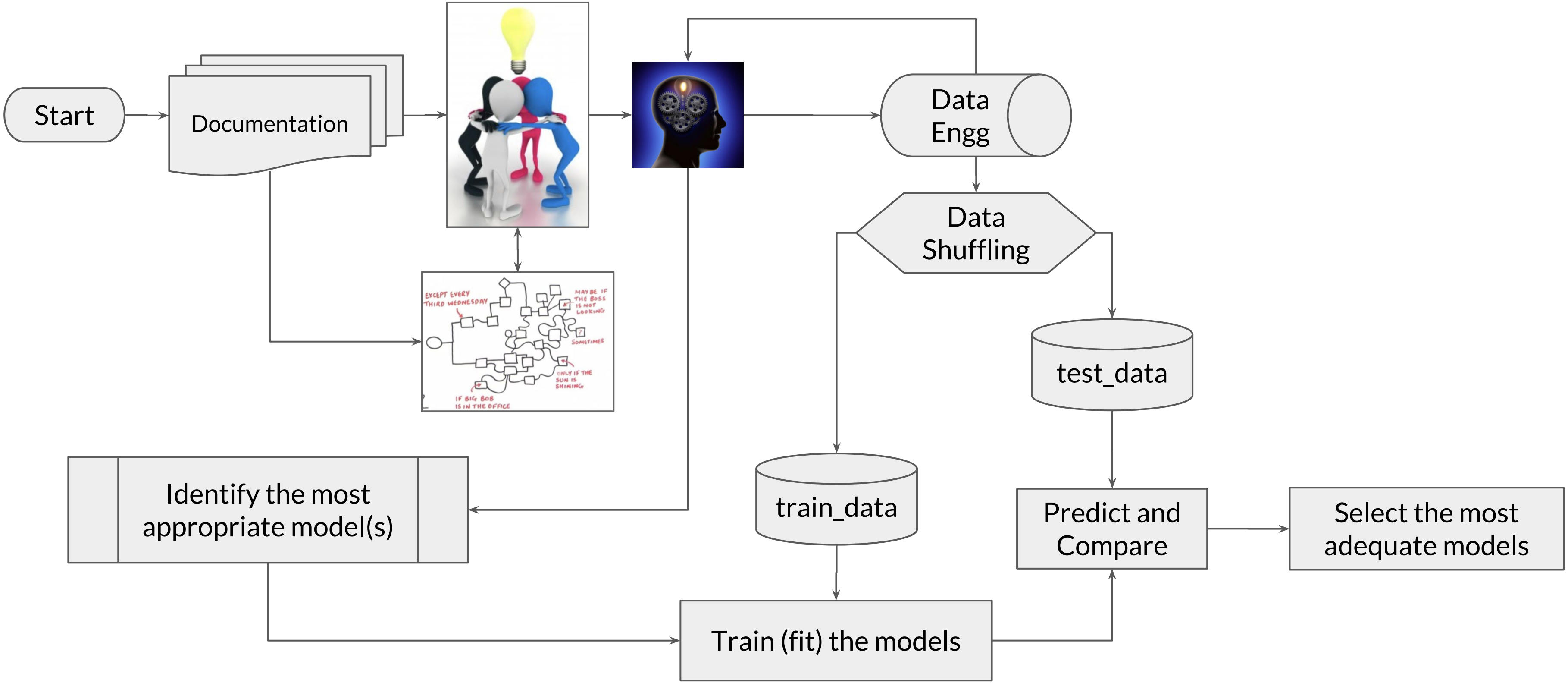
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Select the most adequate models
Train (fit) the models

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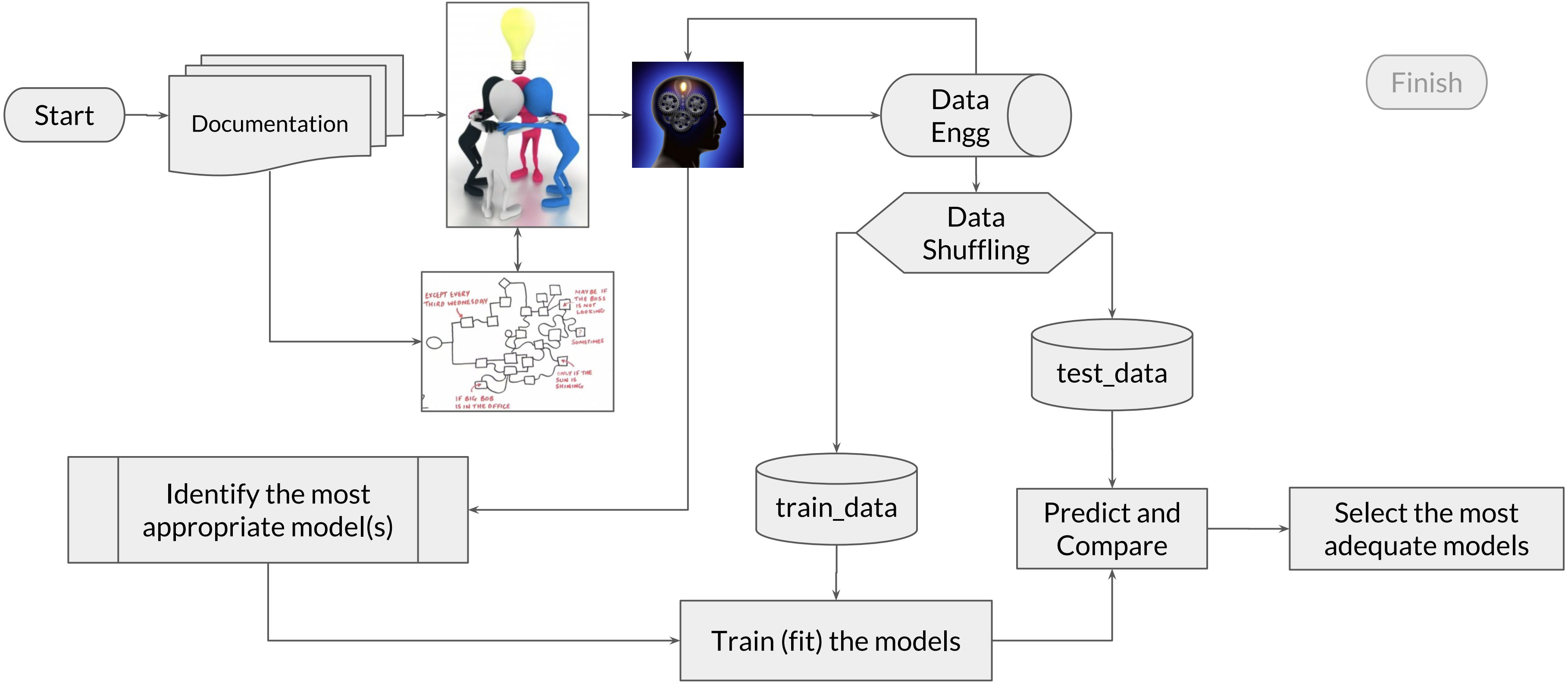

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Identify the most appropriate model(s)

Train (fit) the models

Predict and Compare

Select the most adequate models

Finish

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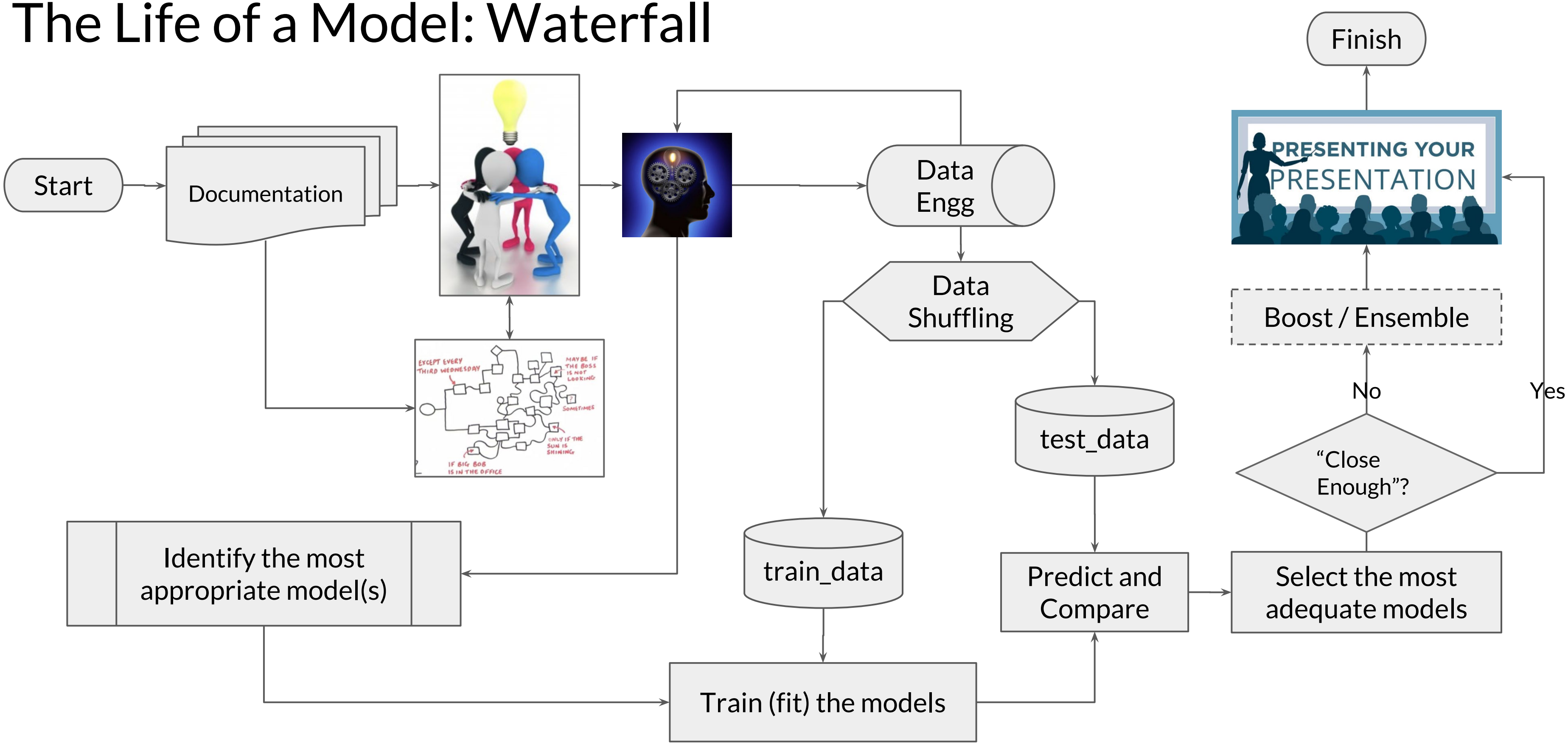

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Identify the most appropriate model(s)

Train (fit) the models

Predict and Compare

Select the most adequate models

"Close Enough"?

No

Yes

Boost / Ensemble

Finish

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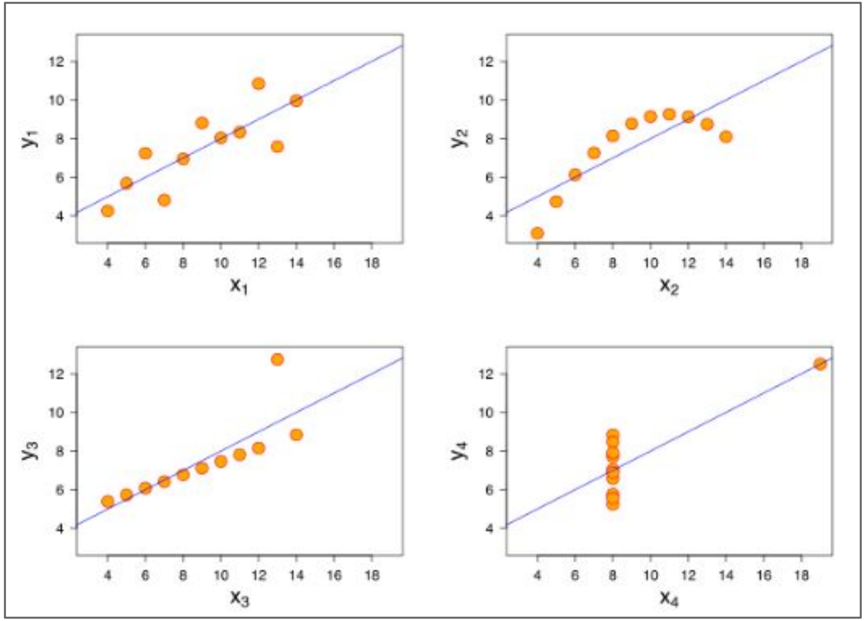
Regression: How to find the Best-Fitting Model

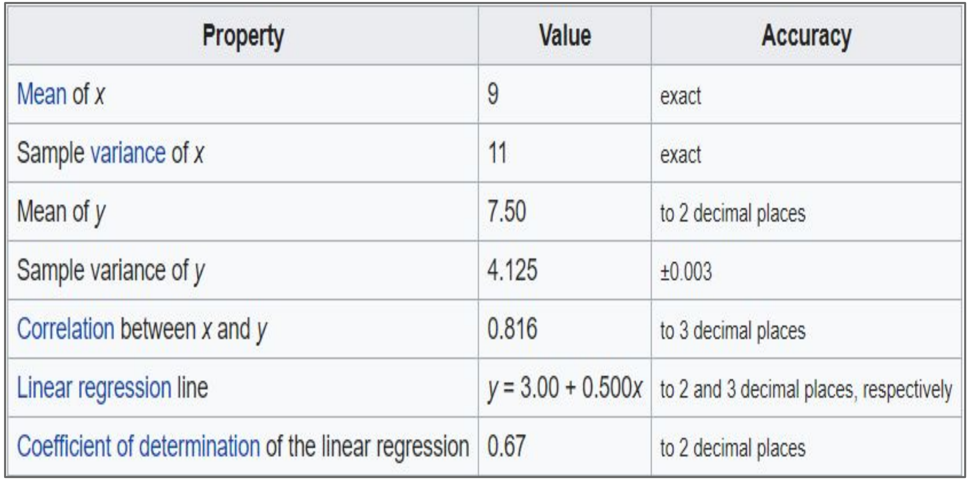
1. The 7 linearizable models
2. Multivariate Analysis
3. Fine points of model selection

Details are here.
More details are here.

Regression: One Thing to Beware



Anscombe's Quartet



Property	Value	Accuracy
Mean of *x*	9	exact
Sample variance of *x*	11	exact
Mean of *y*	7.50	to 2 decimal places
Sample variance of *y*	4.125	±0.003
Correlation between *x* and *y*	0.816	to 3 decimal places
Linear regression line	*y* = 3.00 + 0.500*x*	to 2 and 3 decimal places, respectively
Coefficient of determination of the linear regression	0.67	to 2 decimal places

Classification Model Quality:

Accuracy

True Value	Happy	Unhappy	Total Classified
Happy	6	3	9
Unhappy	4	15	19
Total True	10	18	28

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} = 76\%$$

Classification Model Quality:
Precision

True Value	Happy	Unhappy	Total Classified
Happy	6	3	9
Unhappy	4	15	19
Total True	10	18	28

$$Precision = \frac{TP}{TP + FP}$$

= 67% for Happy
= 79% for Unhappy

Classification Model Quality:
Specificity

True Value	Happy	Unhappy	Total Classified
Happy	6	3	9
Unhappy	4	15	19
Total True	10	18	28

$$\boxed{Specificity = \frac{TN}{TN + FP}}$$

= 33% for Happy

= 21% for Unhappy

Classification Model Quality:
Recall (Sensitivity)

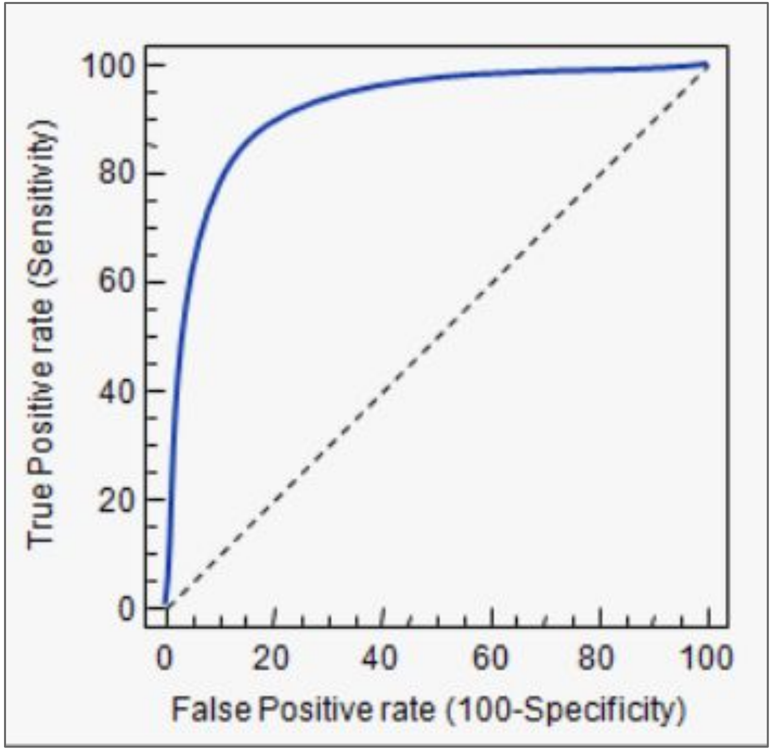
True Value	Happy	Unhappy	Total Classified
Happy	6	3	9
Unhappy	4	15	19
Total True	10	18	28

$$Recall = Sensitivity = \frac{TP}{TP + FN}$$

= 83% (Unhappy)

= 60% (Happy)

Classification Model Quality: AUC (Area Under Curve)



The higher the AUC the more likely we are to recognize the right label and the less likely we are to have a false positive conclusion.

Very useful for multi-label classification.

A great Wikipedia article here: https://en.wikipedia.org/wiki/Receiver_operating_characteristic

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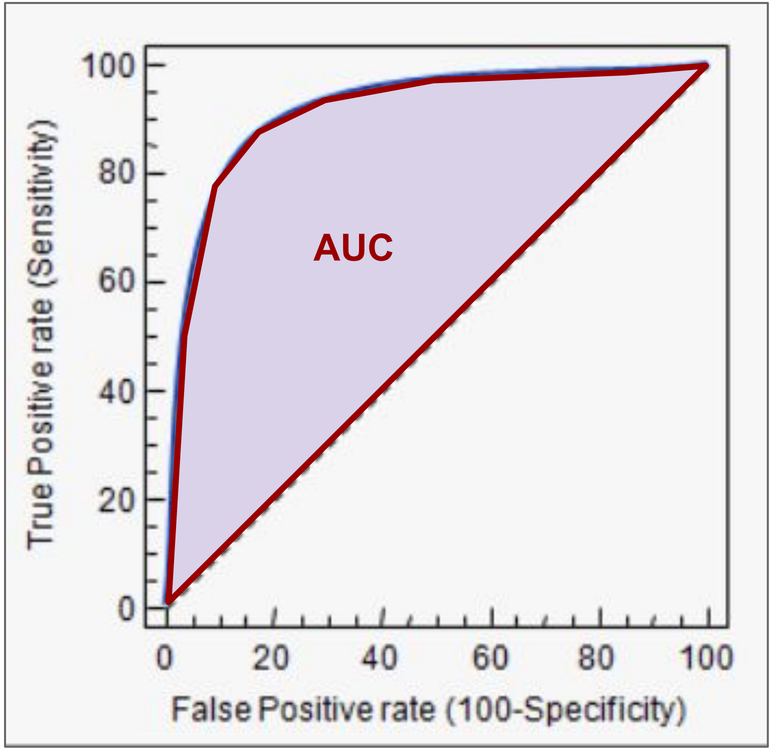

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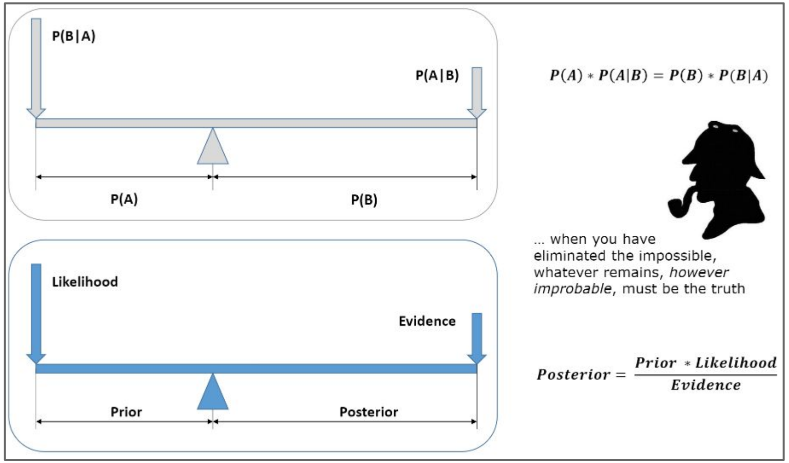
In Lieu of Epilogue:


P(B|A)
P(A|B)
P(A)
P(B)
Likelihood
Evidence
Prior
Posterior
$P(A) * P(A|B) = P(B) * P(B|A)$
$Posterior = \frac{Prior * Likelihood}{Evidence}$

... when you have eliminated the impossible, whatever remains, *however improbable*, must be the truth

1. **Bayesian Principle**
2. **Neural Networks:**
   a. A very short overview of what neural networks are is here.
   b. Naftali Tishby: the only existing mathematical explanation for why Deep Neural Networks work.
3. **Dimensionality Reduction:** Principal Component Analysis (PCA) (a more serious video)

Appendix

A lot of useful PDFs: https://github.com/chemodan/ml_training_for_cmg_impact/tree/master/PDF

An excellent blog: https://sebastianraschka.com/blog/index.html

Q&A sources: Quora; StackOverflow; StackExchange

A good explanation of confidence intervals of variances: (milefoot)

What We Have Discussed

1. Literature
2. Examples:
   a. Linear Regression
   b. Logistic Regression
   c. Classification
   d. Clustering
3. Workflow
4. Model Quality:
   a. Regression
   b. Classification

Where We Skimmed the Surface & What We Left Out

1. Dimensionality Reduction Techniques
2. Neural Networks
3. Bayesian Approach
4. Time Series Analysis
   a. Stationary
   b. Nonstationary
5. Statistical Process Control

Some Additional Useful Links

GitHub repository for this presentation: https://github.com/chemodan/ml_training_for_cmg_impact

Tools (No Programming Needed):

- https://www.knime.com/ - a generic ML platform (GUI-based ML workflow creation tool)
- https://www.youtube.com/watch?v=7IpvQW360js - Word analysis: Wordij (a 25-min demo)
- https://gephi.org/ - a network visualization tool

Thank you!