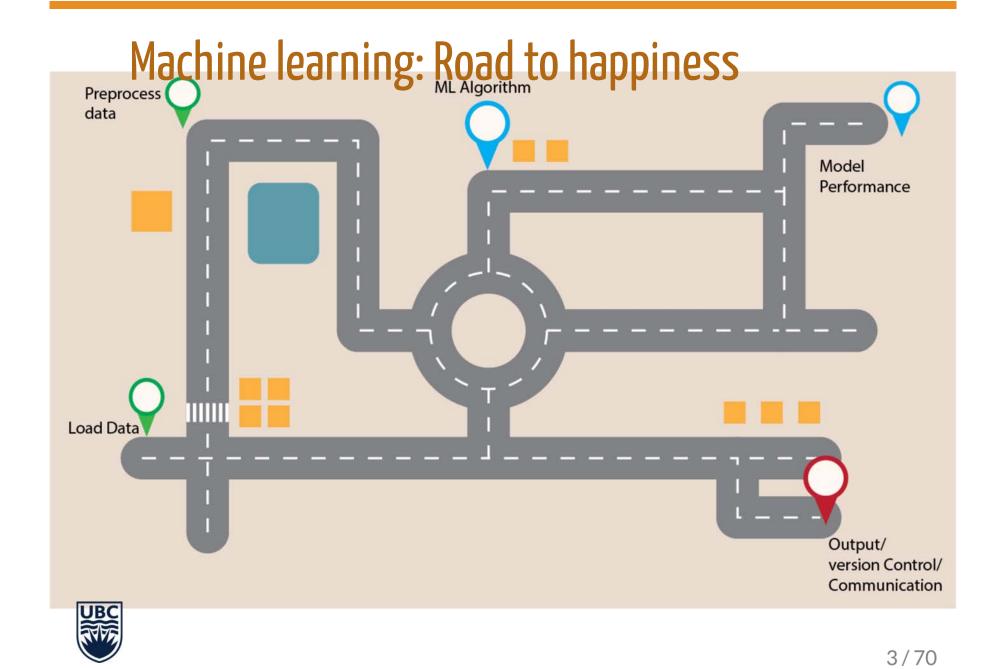




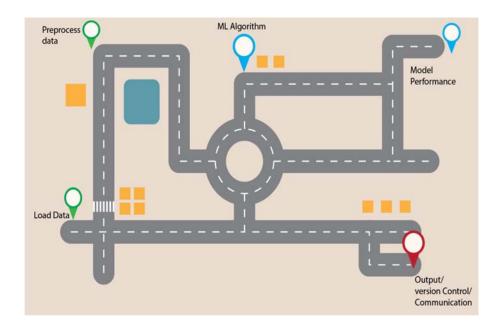
Smart Data

3 Case Studies of Machine Learning in Fundraising Analytics

Claudia Rangel and Mai Bui 2018/7/16 (updated: 2018-08-09)



file:///C:/DAP/apra2018/APRA2018_Slides2.html#69



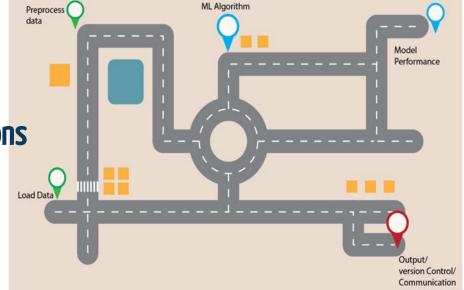


Machine learning: Road to happiness

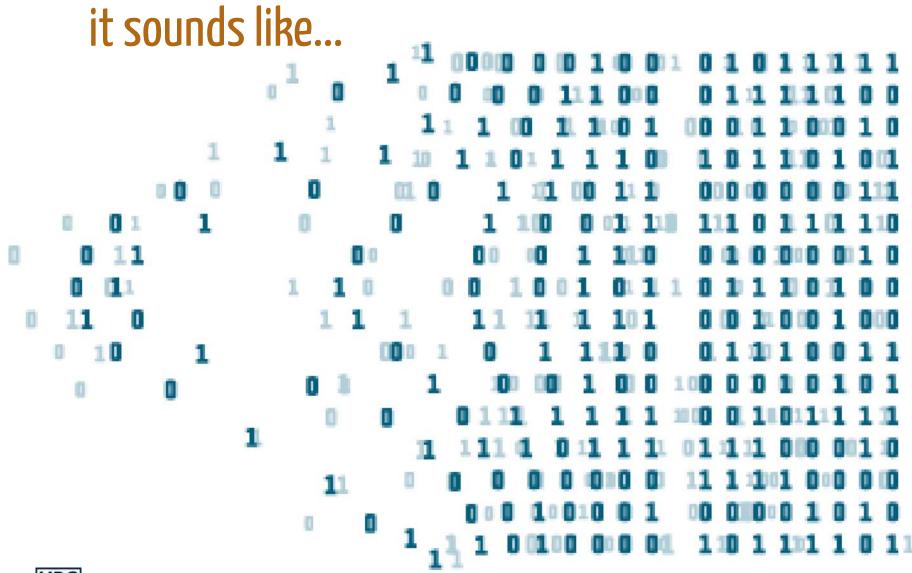
The Vehicle: Machine Learning

The Destination: Analytics questions

The route: ML analysis workflow











Machine learning





Machine learning

Qb Qb

Subfield of Al



Machine learning



- Subfield of Al
- automated learning approaches used to detect patterns in data -algorithms-
- ubiquitous: antispam software; search engines; product recommendation; website chatbots; face detection in phones and cameras...



Machine learning



- Subfield of Al
- automated learning approaches used to detect patterns in data -algorithms-
- ubiquitous: antispam software; search engines; product recommendation; website chatbots; face detection in phones and cameras...
- Concerned with prediction error on new data.

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 Learning the patterns in data, with adjustable parameters tweaks- by optimizing a performance metric -benchmark-

Machine learning



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 Learning the patterns in data, with adjustable parameters tweaks- by optimizing a performance metric -benchmark-

Why Machine learning





Why Machine learning



Data as asset



Why Machine learning



- Data as asset
- Efficiency



Why Machine learning



- Data as asset
- Efficiency
- Automated workflow



Overview of common ML Algorithm



Overview of common ML Algorithm Unsupervised Learning



Overview of common ML Algorithm

ab ab

Unsupervised Learning

- No target variable defined (identifying the different groups). Task focuses on grouping observations (donors, alumni, organizations) to maximize differences within groups.
- Clustering



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• We know what we are looking for (previous donor, event attendee, engaged alum). Task focuses on correctly classifying new observations.



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- Regression



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- Classification
- Regression



 Many others out of intro scope: (Semi-supervised learning, Reinforcement learning, Deep Learning, Adversarial Learning)

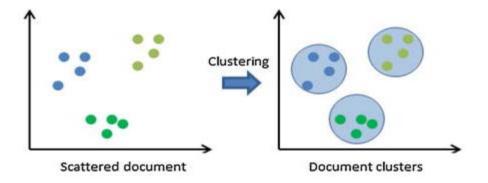
ML: Unsupervised Learning



- K-means
- DBSCAN



Clustering





ML: Supervised Learning





ML: Supervised Learning



Rule-based approach

Decision tree, regression trees, and random forest algorithm.



ML: Supervised Learning



Rule-based approach

Decision tree, regression trees, and random forest algorithm.

Probabilistic approach

Naive Bayes algorithm.



ML: Supervised Learning



Rule-based approach

Decision tree, regression trees, and random forest algorithm.

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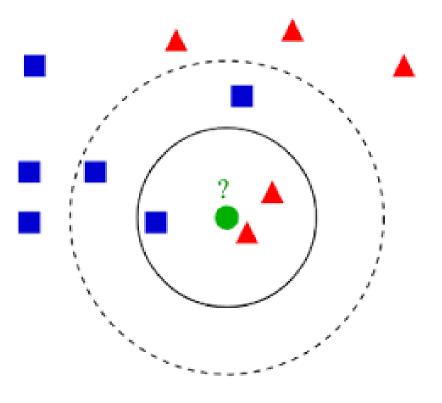
Naive Bayes algorithm.

Distance-based approach

I Support vector machine, KNN

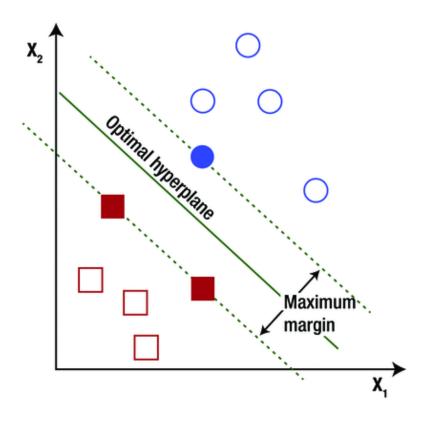


KNN





SVM





ML: Classification Algorithms



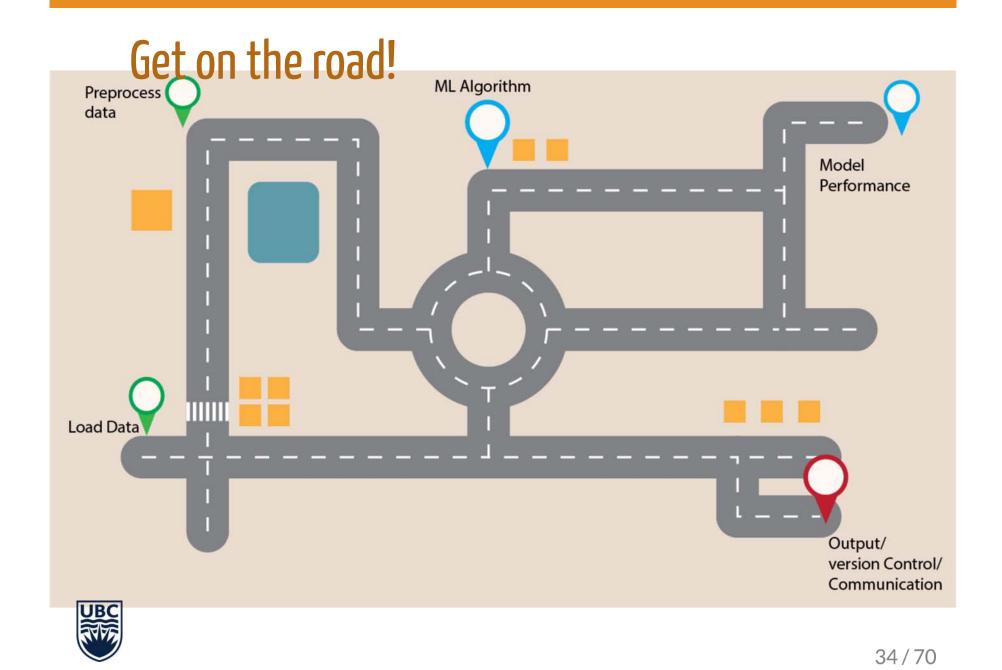
• Ensembles

• Common ML: Random Forest, bagging boosting

• Great: Performance

• Not so great: Interpretability





Choose and setup your stack





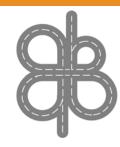
Choose and setup your stack

ab

Python



Choose and setup your stack



- Python
- Conda/miniconda



Choose and setup your stack



- Python
- Conda/miniconda
- IDE, For instance: Jupyter notebook



Choose and setup your stack



- Python
- Conda/miniconda
- IDE, For instance: Jupyter notebook
- · R



Choose and setup your stack



- Python
- Conda/miniconda
- IDE, For instance: Jupyter notebook
- .R
- CRAN
- IDE, for instance: Rstudio



libraries code snippet:

Both RStudio and Jupyter notebooks can handle R and Python code= Great Integration

R

```
pacman:: p_load(rattle,RColorBrewer,rpart.plot,rpart,caret,DMwR,randomForest,e10
```

Python

```
import pandas
import numpy as np
import scipy as sp
import matplotlib.pyplot as plt
import sklearn as sk
```



Why R/Python?



- Not GUI: code once, reuse many -automation, efficiency
- Code IS documentation -reproducibility
- Open source -free!!! Easy to share
- Extensible: committed people creating ready-to-use libraries for data analysis/ML
- Cross-platform



Read Data



--

Import

--

Merge

--

Fuzzy match



Data Prep/Data Wrangling





Data Prep/Data Wrangling



Remove blanks



Data Prep/Data Wrangling



- Remove blanks
- Convert to numeric



Data Prep/Data Wrangling



- Remove blanks
- Convert to numeric
- Check imbalanced target variable -rare outcome-



Data Prep/Data Wrangling



- Remove blanks
- Convert to numeric
- Check imbalanced target variable -rare outcome-
- Run descriptives

--

• Centered/Scale/ Deal with outlier. When appropriate!



	Partition 1	Partition 2	Partition 3
Iteration 1	Train	Train	Test
Iteration 2	Train	Test	Train
Iteration 3	Test	Train	Train



Script model

Partition 1 Partition 2 Partition 3

Iteration 1 Train Train Test

Iteration 2 Train Test Train

Iteration 3 Test Train Train Train



Script model

• Understand how choice of parameter (model options) affect your results.

i.e. number of trees in classification tasks, number of neighbors in KNN task

	Partition 1	Partition 2	Partition 3
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Script model

• Understand how choice of parameter (model options) affect your results.

i.e. number of trees in classification tasks, number of neighbors in KNN task

• Cross-validation is important

Iteration 1	Train	Train	Test
Iteration 2	Train	Test	Train
Iteration 3	Test	Train	Train

Partition 2

Partition 1



Partition 3

Model Performance

Many metrics. Best one depends on your goal.

• Accuracy, ROC, Entropy, Loss Function

			Actual
		1	0
Predicted	1	Α	В
	0	C	D



Version Control: Git - Github - RStudio

"FINAL".doc



FINAL.doc!



FINAL_rev. 2. doc

















FINAL_rev.18.comments7.

FINAL_rev.22.comments49. corrections 9. MORE. 30. doc corrections. 10. #@\$ %WHYDID ICOMETOGRADSCHOOL????.doc

WWW.PHDCOMICS.COM







• Git is a version control system



Files structured in a repository



Git is a version control system



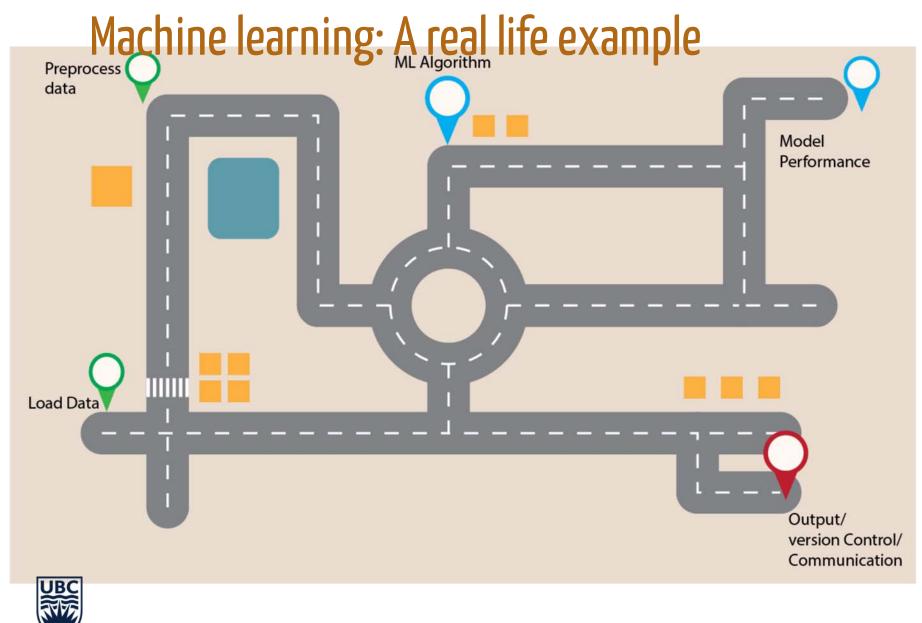
Files structured in a repository

• Github provides a hosting service for your git repositories on the internet. (dropbox loose example).

Functionality: share, synch, make changes

Remote repository that we can go back to, after the feared delete/replace/corrupt local files crises.



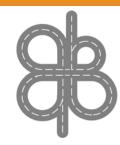


Brainstorming





Brainstorming



• Pick a problem from your *unending* analysis to-do list



Brainstorming



- Pick a problem from your *unending* analysis to-do list
- Choose the ML algorithm that best match the question and data



Brainstorming



- Pick a problem from your *unending* analysis to-do list
- Choose the ML algorithm that best match the question and data
- Think about the nature of the data: preprocessing, imbalanced



Brainstorming



- Pick a problem from your *unending* analysis to-do list
- Choose the ML algorithm that best match the question and data
- Think about the nature of the data: preprocessing, imbalanced
- What is the *first barrier* to start your road to happiness
 - Can we help? DAS community / book resources / specific questions



Next Steps:





Next Steps:

Detailed R and Python notebooks are available in our github site



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- Detailed R and Python notebooks are available in our github site
- Got more time?



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These are some extra Resources



Next Steps:

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These are some extra Resources

Github, Git and Rstudio for version control workflows:

http://happygitwithr.com/

- Rstudio
- Rbloggers, useR



• Stackoverflow, Kaggle





Thanks!

This presentation used xaringan ninja style.

CSS file based on Rladies by Alison Presmanes Hill

69 / 70 00:50