

# DATA SCIENCE

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# ML in Production - Deployment

(Ref: The most under-taught skill in machine learning - George Seif )

## After Learning Machine Learning

- ▶ Once you create your machine learning algorithm, that research part is done.
- ▶ Then you really start the bulk of the work.
- ▶ How will the results of your model be delivered to the end user?
- ▶ In today's world you'll need some powerful hardware to be able to run it at a reasonable speed; that means running your machine learning API on the cloud.
- ▶ That's called "putting it in Production" or "Deployment"

## Whats needed

- ▶ In today's world you'll need some powerful hardware to be able to run it at a reasonable speed;
- ▶ That means running your machine learning API on the cloud.
- ▶ You run it on a cloud server and send the results back to the user!
- ▶ You automate your system pipeline and have it ready to automatically scale based on your user traffic!
- ▶ Cloud computing is the workhorse behind the real-world machine learning applications.

## Cloud computing for machine learning



## Cloud Players

- ▶ AWS: most popular, allows you to control and customize
- ▶ Azure: Offers you easy of use at the expense of a bit of control and customization.
- ▶ GCP is somewhere in the middle of the two with some abstraction but not too much.

## AWS EC2

- ▶ Houses your machine learning servers.
- ▶ Set up your machine learning model on the server.
- ▶ When you want to run something on your model, you send the data you want processed to the server, your model processes it, and sends it back to the user!
- ▶ EC2 also offers auto-scaling so that you can automatically spawn more or less servers based on the demand

## AWS Lambda

- ▶ With lambda, you can basically set up automated trigger functions which will only run when a certain condition is met.
- ▶ For example, have your lambda function send an email to your user only when a certain results comes up from your machine learning module, such as some critical situation



## AWS S3

Very cheap, 99.9999999% up-time, with fast download and upload speeds!

## AWS RDS

Managed Relational Database Service for MySQL, PostgreSQL, Oracle, SQL Server, and MariaDB. Organize all of your important data for your machine learning data, API, infrastructure, and model results here.

## AWS CodeDeploy

Automatically have your code and new machine learning models deployed to your servers as soon as you commit them to GitHub

## AWS Cloudwatch

Online logs to constantly monitor your machine learning system

## Amazon Simple Queue Service (SQS)

A queue hosted in the cloud. Keep your machine learning jobs organised and in order using a cloud queue

## AWS Mobile Hub

Build, test, and monitor your apps remotely using the cloud. Just log in to your AWS account without the hassle of pulling data from your app manually

## Amazon API Gateway

Build, deploy, and manage your API at any scale in the cloud. Have all the information you need for this in one simple place

## Amazon Sagemaker

Build, train, and test your machine learning models using a high-level easy to use interface



## What Next?

- ▶ Coursera has a great one on GCP and Udemy has one on AWS!
- ▶ As always, it's a great idea to actually use the platform to learn it best.
- ▶ AWS offers a free tier for a year and their service aren't too expensive if you would like to play around with some of the non-free ones.
- ▶ GCP offers \$300 of free credits for new accounts too!

# Conclusion

# What did you learn?

## Machine Learning

From [xkcd](#)



# ML Recap

(Ref: "Machine Learning Algorithm Cheat Sheet" - Laura Diane Hamilton)

# Linear regression

Theme: Fitting Line

## Pros

- ▶ Very fast (runs in constant time)
- ▶ Easy to understand the model
- ▶ Less prone to over-fitting

## Cons

- ▶ Unable to model complex relationships
- ▶ Unable to capture nonlinear relationships without first transforming the inputs

## Good at

- ▶ The first look at a dataset
- ▶ Numerical data with lots of features

# Decision trees

Theme: Fitting a tree

## Pros

- ▶ Fast
- ▶ Robust to noise and missing values
- ▶ Accurate

## Cons

- ▶ Complex trees are hard to interpret
- ▶ Duplication within the same sub-tree is possible

## Good at

- ▶ Medical diagnosis
- ▶ Credit risk analysis

# Support Vector Machines

Theme: Partitioning Hyperplanes with wide margins

## Pros

- ▶ Can model complex, nonlinear relationships
- ▶ Robust to noise (because they maximize margins)

## Cons

- ▶ Need to select a good kernel function
- ▶ Model parameters are difficult to interpret

## Good at

- ▶ Handwriting recognition
- ▶ Text classification

# K-Nearest Neighbors

Theme: Partitioning Hyperplanes with wide margins

## Pros

- ▶ Simple, Powerful
- ▶ No training involved ("lazy")
- ▶ Naturally handles multiclass classification and regression

## Cons

- ▶ Expensive and slow to predict new instances
- ▶ Performs poorly on high-dimensionality datasets
- ▶ Must define a meaningful distance function

## Good at

- ▶ Low-dimensional datasets
- ▶ Fault detection



## Comparing ML Algorithms

- ▶ Power and Expressibility: ML methods differ in terms of complexity. Linear regression fits linear functions while NN define piecewise-linear separation boundaries. More complex models can provide more accurate models, but at the risk of over-fitting.
- ▶ Interpret-ability: some models are more transparent and understandable than others (white box vs. black box models)
- ▶ Ease of Use: some models feature few parameters/decisions (linear regression/NN), while others require more decision making to optimize (SVMs)
- ▶ Training Speed: models differ in how fast they fit the necessary parameters
- ▶ Prediction Speed: models differ in how fast they make predictions given a query

(pto ...)

## KNN Regression Example: 1d

Method	Power of Expression	Ease of Interpretation	Ease of Use	Training Speed	Prediction Speed
Linear Regression	5	9	9	9	9
Nearest Neighbor	5	9	8	10	2
Naive Bayes	4	8	7	9	8
Decision Trees	8	8	7	7	9
Support Vector Machines	8	6	6	7	7
Boosting	9	6	6	6	6
Graphical Models	9	8	3	4	4
Deep Learning	10	3	4	3	7

What Next?

# Machine Learning Journey

## To start with . . .

- ▶ If you want a more practical route then: Udacity Intro to Machine Learning
- ▶ If you want to learn Machine Learning in-depth then: Coursera Machine Learning Andrew Ng
- ▶ If you want other free courses, blogs, and books then: Phoenixts
- ▶ After being familiar with that, you should try learning:
  - ▶ How to Approach Almost Any ML Problem - Abhishek Thakur
  - ▶ Bias Variance Trade-Off  
<http://scott.fortmann-roe.com/docs/BiasVariance.html>
  - ▶ Measuring Errors <http://scott.fortmann-roe.com/docs/MeasuringError.html>
  - ▶ ROC Curve & AUC Explained  
<https://www.youtube.com/watch?v=OAl6eAyP-yo>

(Ref: "Simple 8 Step guide to learn Machine Learning with Python" - Randy Lao)

# Machine Learning Learning Path

After you are done with Python ...

- ▶ Machine Learning in 20min: <https://www.youtube.com/watch?v=MOdlp1d0PNA>
- ▶ Skcikit-Learn Tutorial: <https://www.youtube.com/watch?v=el0jMn4kk>
- ▶ Kaggle Machine Learning Tutorial: <https://www.kaggle.com/learn/machine-learning>
- ▶ Google Crash cours Machine Learning
- ▶ Machine Learning at Berkeley <https://ml.berkeley.edu/blog/tutorials/>
- ▶ How to Learn Machine Learning in 6 Months  
<https://www.youtube.com/watch?v=MOdlp1d0PNA&t=584s>
- ▶ Learning Machine Learning & AI Guideline  
<https://www.youtube.com/watch?v=PYKfXkd3t7c>
- ▶ edX – Machine Learning (Columbia University, John Paisley)  
<https://www.edx.org/course/machine-learning-columbiacx-cs111-102x-0>
- ▶ sentdex – Practical Machine Learning Tutorial (Youtube)

(Ref: "To start your DataScience Journey" - Randy Lao)

## Transitioning into DataScience

Some amazing advice for those transitioning into DataScience: ...

- ▶ Kyle McKiou - DS Interview
- ▶ Sarah Nooravi - Personal Skills
- ▶ Beau Walker - How to Gain Experience
- ▶ Eric Weber - DS Companies
- ▶ Vin Vashishta - DS Interviews & Your Persona
- ▶ Kevin Tran - How to Land Your 1st DS Job
- ▶ David Langer - The 80/20 Rule of DS
- ▶ Favio Vázquez - Persistence
- ▶ Nic Ryan - Your Game Plan

(Ref: "Transitioning into DataScience" - Randy Lao)

# Conculsion

## Recipe Tour

Here, you will see 5 recipes of supervised classification algorithms applied to small standard datasets that are provided with the scikit-learn library. Each example is:

- ▶ **Standalone:** Each code example is a self-contained, complete and executable recipe.
- ▶ **Just Code:** The focus of each recipe is on the code with minimal exposition on machine learning theory.
- ▶ **Simple:** Recipes present the common use case, which is probably what you are looking to do.
- ▶ **Consistent:** All code example are presented consistently and follow the same code pattern and style conventions.



# Logistic Regression

Logistic regression fits a logistic model to data and makes predictions about the probability of an event (between 0 and 1).

```
1 from sklearn import datasets
  from sklearn import metrics
3 from sklearn.linear_model import LogisticRegression

5 dataset = datasets.load_iris()

7 model = LogisticRegression()
  model.fit(dataset.data, dataset.target)
9 print(model)

11 expected = dataset.target
   predicted = model.predict(dataset.data)
13
   print(metrics.classification_report(expected, predicted))
15 print(metrics.confusion_matrix(expected, predicted))
```

# Naive Bayes

Naive Bayes uses Bayes Theorem to model the conditional relationship of each attribute to the class variable. This recipe shows the fitting of an Naive Bayes model to the iris dataset.

```
1 from sklearn import datasets
  from sklearn import metrics
3 from sklearn.naive_bayes import GaussianNB

5 dataset = datasets.load_iris()

7 model = GaussianNB()
  model.fit(dataset.data, dataset.target)
9 print(model)

11 expected = dataset.target
   predicted = model.predict(dataset.data)
13
   print(metrics.classification_report(expected, predicted))
15 print(metrics.confusion_matrix(expected, predicted))
```

## k-Nearest Neighbor

The k-Nearest Neighbor (kNN) method makes predictions by locating similar cases to a given data instance (using a similarity function) and returning the average or majority of the most similar data instances.

```
1 from sklearn import datasets
  from sklearn import metrics
3 from sklearn.neighbors import KNeighborsClassifier

5 dataset = datasets.load_iris()

7 model = KNeighborsClassifier()
  model.fit(dataset.data, dataset.target)
9 print(model)

11 expected = dataset.target
   predicted = model.predict(dataset.data)
13
   print(metrics.classification_report(expected, predicted))
15 print(metrics.confusion_matrix(expected, predicted))
```

## Classification and Regression Trees

Classification and Regression Trees (CART) are constructed from a dataset by making splits that best separate the data for the classes or predictions being made.

```
1 from sklearn import datasets
  from sklearn import metrics
3 from sklearn.tree import DecisionTreeClassifier

5 dataset = datasets.load_iris()

7 model = DecisionTreeClassifier()
  model.fit(dataset.data, dataset.target)
9 print(model)

11 expected = dataset.target
   predicted = model.predict(dataset.data)
13
14 print(metrics.classification_report(expected, predicted))
15 print(metrics.confusion_matrix(expected, predicted))
```

## Support Vector Machines

Support Vector Machines (SVM) are a method that uses points in a transformed problem space that best separate classes into two groups.

```
1 from sklearn import datasets
  from sklearn import metrics
3 from sklearn.svm import SVC

5 dataset = datasets.load_iris()

7 model = SVC()
  model.fit(dataset.data, dataset.target)
9 print(model)

11 expected = dataset.target
   predicted = model.predict(dataset.data)
13

   print(metrics.classification_report(expected, predicted))
15 print(metrics.confusion_matrix(expected, predicted))
```

## Benefits and drawbacks of scikit-learn

### Benefits

- ▶ Consistent interface to machine learning models
- ▶ Provides many tuning parameters but with sensible defaults
- ▶ Exceptional documentation
- ▶ Rich set of functionality for companion tasks
- ▶ Active community for development and support

### Potential drawbacks

- ▶ Harder (than R) to get started with machine learning
- ▶ Less emphasis (than R) on model interpret-ability

## Essential Machine Learning Algorithms

After you are done with Python ... Here is a list of 10 Essential Algorithms that you should know to understand the basics of MachineLearning:

- ▶ Logistic Regression <https://lnkd.in/gJ2BwhD>
- ▶ Linear Regression <https://lnkd.in/gdZDbT5>
- ▶ Decision Trees <https://lnkd.in/gwadA-p>
- ▶ Random Forests <https://lnkd.in/gRYHcvt>
- ▶ Neural Networks <https://lnkd.in/gZQhWyv>
- ▶ Bayesian Techniques <https://lnkd.in/gY3qVYP>
- ▶ Support Vector Machines <https://lnkd.in/gWJKRyn>
- ▶ Gradient Boosting Machine <https://lnkd.in/gv85yDV>
- ▶ K-Nearest Neighbors <https://lnkd.in/gsiyqcM>
- ▶ Regularized Linear Models <https://lnkd.in/g3fn3cr>

(Ref: "Essential Machine Learning Algorithms" - Randy Lao)

# Kaggle Datasets and Projects

- ▶ Binary Classification
  - ▶ Indian Liver Patient Data <https://bit.ly/2OvwYtm>
  - ▶ Financial Data - Fraud Detection <https://bit.ly/2lyg2x0>
  - ▶ Predict Product Backorders? <https://bit.ly/2OqMwie>
  - ▶ Adult Census Income <https://bit.ly/2zLAKXB>
- ▶ Multi-Classification
  - ▶ Iris <https://bit.ly/2xS1xQn>
  - ▶ Fall Detection <https://bit.ly/2lrxEP>
  - ▶ Biomechanical Features of Ortho Patients <https://bit.ly/2Hqv9ep>
- ▶ Regression
  - ▶ Video Game Sales <https://bit.ly/2qsu2OR>
  - ▶ NYC Property Sales <https://bit.ly/2AKijRz>
  - ▶ Gas Sensors <https://bit.ly/2OvYlhm>
- ▶ NLP
  - ▶ The Enron Email Dataset <https://bit.ly/2xS3gVR>
  - ▶ Ubuntu Dialogue Corpus <https://bit.ly/2ygxBx1>
  - ▶ Old Newspapers <https://bit.ly/2NXCDcg>
  - ▶ Blog Authorship Corpus <https://bit.ly/2y4t4xr>
- ▶ Time Series
  - ▶ Crypto Historical Data <https://bit.ly/2y5tzYb>
  - ▶ Exoplanet Hunting in Deep Space <https://bit.ly/2RoOD4K>
- ▶ Image Processing
  - ▶ YouTube Faces <https://bit.ly/2QvLYeF>



# Machine Learning Projects

Last one is a MUST DO! ...

- ▶ Pokemon - Weedle's Cave
- ▶ Titanic ML
- ▶ Housing Prices Prediction
- ▶ Instacart Market Basket Analysis
- ▶ Quora Question Pairs
- ▶ Human Resource Analytics
- ▶ Analyzing Soccer Player Faces
- ▶ Recruit Restaurant Visitor Forecasting
- ▶ TensorFlow Speech Recognition
- ▶ Yourself: The BEST project you'll ever work on is you.

(Ref: "10 GREAT DataScience Projects to work on" - Randy Lao)

## Machine Learning Dataset sites

### Got Data? ...

- ▶ UCI Machine Learning Repository <https://archive.ics.uci.edu/ml/datasets.html>
- ▶ Kaggle: <https://www.kaggle.com/datasets>
- ▶ Quandl: The premier source for financial, economic, and alternative datasets  
<https://www.quandl.com/>
- ▶ KDD Cup Archives: Archives of the Data Mining and Knowledge Discovery competition  
<http://www.kdd.org/kdd-cup>
- ▶ Data Driven: Datasets where data science can be used to create a social impact  
<https://lnkd.in/gGtpN9q>
- ▶ Data Gov The home of the U.S. Government's open data <https://www.data.gov/>

(Ref: "Top 6 websites to get datasets for Machine Learning" - Randy Lao)

# Machine Learning Websites

## Favorite websites to learn from . . .

- ▶ FastML - Machine Learning Made Easy
- ▶ Analytics Vidhya - Learning Everything About Analytics
- ▶ Machine Learning Mastery - Title Explains It
- ▶ KDNuggets - One of the most popular Data Science blogs
- ▶ Data Science Central - Online Resource for Big Data Practitioners
- ▶ Data at Quora - Where Data Scientists Share What They've Learned
- ▶ Towards Data Science - Sharing Data Science Concepts, Ideas, and Codes

(Ref: "7 Favorite websites to learn from" - Randy Lao)

## Machine Learning Youtube channels

Favorite video lists to learn from ...

- ▶ 3Blue1Brown Essence of Linear Algebra
- ▶ StatQuest (Joshua Starmer) Statistics Made EASY
- ▶ Siraj Raval Fun Machine Learning & AI
- ▶ Analytics University Anything Analytics & Machine Learning
- ▶ AlphaOpt Optimization & Gradient Descent (Short and easy explanation)
- ▶ 3Blue1Brown Simple Visual Explanation on Neural Networks
- ▶ Two Minute Papers Awesome AI Research For Everyone

(Ref: "My Favorite resources on Youtube" - Randy Lao)

## References

Many publicly available resources have been refereed for making this presentation. Some of the notable ones are:

- ▶ Introduction to Machine Learning with scikit.learn - West of Ireland Data Science
- ▶ STAT 365/665: Data Mining and Machine Learning - Taylor Arnold
- ▶ CSC 600: Data Mining - Richard Burns
- ▶ Data Science Simplified - Pradeep Menon
- ▶ Learn Data Science - Nitin Borwankar
- ▶ IAML: Decision Trees - Victor Lavrenko and Charles Sutton
- ▶ Data Science Notebooks
- ▶ Analytics Vidhya Blogs
- ▶ Machine Learning - Brett Wujek , SAS Institute
- ▶ Introduction to Entropy for Data Science - Mike Schulte

Thanks . . .

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