THE ALL-IN-ONE

PYTHON 3, DATA ANALYTICS, DATA SCIENCE, MACHINE LEARNING, and DEEP LEARNING

CHEAT ~~SHEET~~

BOOK

This Book Was Prepared By:

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----------SUMMARY----------

I combine curiosity, with passion to build solutions that meet critical challenges. I believe that Machine Learning is a tool that will continue to grow in importance, and I am excited to apply it to important problems.

----------SKILLS----------

PROGRAMMING:

OO Design, Data Structures, Algorithms, Space and Time Complexities, Python, NumPy, Matplotlib, SQL, Scala, AWS, Google Cloud, Jupyter Notebook, APIs, Git, Linux/Unix CLI

DATA:

ETL, Strategy and Planning, Data Mining and Collection, Data Engineering, Data Cleaning, Data Integrity, Data Processing, Data Visualizations and Charts, Excel, Tableau, Communication and Presentation (Technical and Non-Technical)

MACHINE LEARNING:

Keras, TensorFlow, Classification Modeling, Regression Modeling, Supervised Learning, Unsupervised Learning, Ensemble Methods, Neural Networks, NLP, Image Classification, Machine Vision, Time-series, Forecasting

----------TECHNICAL PROJECTS----------

NJ Transit NJCL Track Informer (*Python*)

I created a customer-centered product that connects with the Twitter API and posts the which track the train will be arriving at. I have received over 20k impressions in the first 48 hours.

Analysis of Colorectal Cancer (*Python*)

After conducting research, we have created several pipelines in Python to run biostatistical and machine learning analyses to analyze the health of the Colorectal cancer patients.

Salary Predictor (*Python*)

I designed an app that allows users to upload their resume, choose an algorithm, and get an estimated annual salary. The algorithms were trained on over 6,000 tech and development jobs. This app can is accessible on https://salary.jackbibi.dev

----------EXPERIENCE----------

DEVRY UNIVERSITY – *Curriculum Developer* ***09/2019 – Present***

I develop course material and roadmaps for technical courses in the areas of Data Science, Machine Learning, and Software Development. These courses are python-based and use Tensorflow and other Python libraries.

GENIEOUSLY – *Data Science Internship* **05/2019 – 09/*2019***

I created forecasting algorithms for clients to assist in Stock Management, Predict Cost, and give an Accurate Pricing Estimate to customers.

OUTDOOR INTL – *VP of Marketing and Analytics* ***06/2017 –02/2019***

I created content, managed, analyzed, and optimized many social media advertisements on Facebook, Instagram, Twitter, and Google SEO.

SOUTHERN TELECOM – *Marketing and Analytics Engineer* ***03/2015 – 01/2017***

I researched to find the target audience, target price-point, and desired features of specific product categories to maximize sales. My research increased sales by $5 million in 12 months by focusing on hot product and taking early advantage of the FAD

----------EDUCATION----------

DEEP LEARNING SPECIALIZATION by Andrew Ng ***Coursera 2019***

Completed the 5 course specialization in Neural Networks and Deep Learning

ALGORITHMIC TOOLBOX by UC San Diego ***Coursera 2019***

Data Structures & Algorithms Certificate of Completion 2019

GENERAL ASSEMBLY ***02/2019 - 05/2019***

Completed a full-time 500+ hour Data Science Immersive program in Python

BERNARD M. BARUCH COLLEGE (CUNY)

BBA Digital Marketing

Data Science Cheatsheet

Compiled by Maverick Lin (http://mavericklin.com)

Last Updated August 13, 2018

What is Data Science?

Multi-disciplinary field that brings together concepts from computer science, statistics/machine learning, and data analysis to understand and extract insights from the ever-increasing amounts of data.

Two paradigms of data research.

1. **Hypothesis-Driven:** Given a problem, what kind of data do we need to help solve it?
2. **Data-Driven:** Given some data, what interesting problems can be solved with it?

The heart of data science is to always ask questions. Always be curious about the world.

1. What can we learn from this data?
2. What actions can we take once we find whatever it is we are looking for?

Types of Data

Structured: Data that has predefined structures. e.g. tables, spreadsheets, or relational databases.
Unstructured Data: Data with no predefined structure, comes in any size or form, cannot be easily stored in tables. e.g. blobs of text, images, audio
Quantitative Data: Numerical. e.g. height, weight
Categorical Data: Data that can be labeled or divided into groups. e.g. race, sex, hair color.
Big Data: Massive datasets, or data that contains greater *variety* arriving in increasing *volumes* and with ever-higher *velocity* (3 Vs). Cannot fit in the memory of a single machine.

Data Sources/Fomats

Most Common Data Formats CSV, XML, SQL, JSON, Protocol Buffers
Data Sources Companies/Proprietary Data, APIs, Government, Academic, Web Scraping/Crawling

Main Types of Problems

Two problems arise repeatedly in data science.
Classification: Assigning something to a discrete set of possibilities. e.g. spam or non-spam, Democrat or Republican, blood type (A, B, AB, O)
Regression: Predicting a numerical value. e.g. someone's income, next year GDP, stock price

Probability Overview

Probability theory provides a framework for reasoning about likelihood of events.

Terminology

Experiment: procedure that yields one of a possible set of outcomes e.g. repeatedly tossing a die or coin
Sample Space S: set of possible outcomes of an experiment e.g. if tossing a die, S = (1,2,3,4,5,6
Event E: set of outcomes of an experiment e.g. event that a roll is 5, or the event that sum of 2 rolls is 7
Probability of an Outcome s or P(s): number that satisfies 2 properties

1. for each outcome s, $0 \leq \text{P(s)} \leq 1$
2. $\sum$ p(s) = 1

Probability of Event E: sum of the probabilities of the outcomes of the experiment: $\text{p(E)} = \sum_{s \subset E} \text{p(s)}$
Random Variable V: numerical function on the outcomes of a probability space
Expected Value of Random Variable V: $\text{E(V)} = \sum_{s \subset S} \text{p(s)} * \text{V(s)}$

Independence, Conditional, Compound

Independent Events: A and B are independent iff:

$$\text{P(A} \cap \text{B)} = \text{P(A)P(B)}$$
$$\text{P}(A|B) = \text{P(A)}$$
$$\text{P}(B|A) = \text{P(B)}$$

Conditional Probability: $\text{P}(A|B) = \text{P(A,B)/P(B)}$
Bayes Theorem: $\text{P}(A|B) = \text{P}(B|A)\text{P(A)/P(B)}$
Joint Probability: $\text{P(A,B)} = \text{P}(B|A)\text{P(A)}$
Marginal Probability: P(A)

Probability Distributions

Probability Density Function (PDF) Gives the probability that a rv takes on the value x: $p_X(x) = P(X = x)$
Cumulative Density Function (CDF) Gives the probability that a random variable is less than or equal to x: $F_X(x) = P(X \leq x)$
Note: The PDF and the CDF of a given random variable contain exactly the same information.

Descriptive Statistics

Provides a way of capturing a given data set or sample. There are two main types: **centrality** and **variability** measures.

Centrality

Arithmetic Mean Useful to characterize symmetric distributions without outliers $\mu_X = \frac{1}{n}\sum x$
Geometric Mean Useful for averaging ratios. Always less than arithmetic mean $= \sqrt[n]{a_1 a_2 ... a_3}$
Median Exact middle value among a dataset. Useful for skewed distribution or data with outliers.
Mode Most frequent element in a dataset.

Variability

Standard Deviation Measures the squares differences between the individual elements and the mean

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \overline{x})^2}{N-1}}$$

Variance $\text{V} = \sigma^2$

Interpreting Variance

Variance is an inherent part of the universe. It is impossible to obtain the same results after repeated observations of the same event due to random noise/error. Variance can be explained away by attributing to sampling or measurement errors. Other times, the variance is due to the random fluctuations of the universe.

Correlation Analysis

Correlation coefficients r(X,Y) is a statistic that measures the degree that Y is a function of X and vice versa. Correlation values range from -1 to 1, where 1 means fully correlated, -1 means negatively-correlated, and 0 means no correlation.
Pearson Coefficient Measures the degree of the relationship between linearly related variables

$$\text{r} = \frac{Cov(X,Y)}{\sigma(X)\sigma(Y)}$$

Spearman Rank Coefficient Computed on ranks and depicts monotonic relationships

Note: Correlation does not imply causation!

Data Cleaning

Data Cleaning is the process of turning raw data into a clean and analyzable data set. "Garbage in, garbage out." Make sure garbage doesn't get put in.

Errors vs. Artifacts

1. **Errors:** information that is lost during acquisition and can never be recovered e.g. power outage, crashed servers
2. **Artifacts:** systematic problems that arise from the data cleaning process. these problems can be corrected but we must first discover them

Data Compatibility

Data compatibility problems arise when merging datasets. Make sure you are comparing "apples to apples" and not "apples to oranges". Main types of conversions/unifications:

- **units** (metric vs. imperial)
- **numbers** (decimals vs. integers),
- **names** (John Smith vs. Smith, John),
- **time/dates** (UNIX vs. UTC vs. GMT),
- **currency** (currency type, inflation-adjusted, dividends)

Data Imputation

Process of dealing with missing values. The proper methods depend on the type of data we are working with. General methods include:

- Drop all records containing missing data
- Heuristic-Based: make a reasonable guess based on knowledge of the underlying domain
- Mean Value: fill in missing data with the mean
- Random Value
- Nearest Neighbor: fill in missing data using similar data points
- Interpolation: use a method like linear regression to predict the value of the missing data

Outlier Detection

Outliers can interfere with analysis and often arise from mistakes during data collection. It makes sense to run a "sanity check".

Miscellaneous

Lowercasing, removing non-alphanumeric, repairing, unidecode, removing unknown characters

Note: When cleaning data, always maintain both the raw data and the cleaned version(s). The raw data should be kept intact and preserved for future use. Any type of data cleaning/analysis should be done on a copy of the raw data.

Feature Engineering

Feature engineering is the process of using domain knowledge to create features or input variables that help machine learning algorithms perform better. Done correctly, it can help increase the predictive power of your models. Feature engineering is more of an art than science. FE is one of the most important steps in creating a good model. As Andrew Ng puts it:

"Coming up with features is difficult, time-consuming, requires expert knowledge. 'Applied machine learning' is basically feature engineering."

Continuous Data

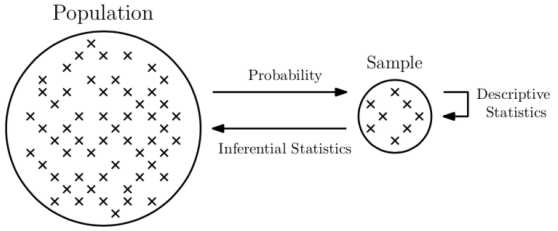
Raw Measures: data that hasn't been transformed yet
Rounding: sometimes precision is noise; round to nearest integer, decimal etc..
Scaling: log, z-score, minmax scale
Imputation: fill in missing values using mean, median, model output, etc..
Binning: transforming numeric features into categorical ones (or binned) e.g. values between 1-10 belong to A, between 10-20 belong to B, etc.
Interactions: interactions between features: e.g. subtraction, addition, multiplication, statistical test
Statistical: log/power transform (helps turn skewed distributions more normal), Box-Cox
Row Statistics: number of NaN's, 0's, negative values, max, min, etc
Dimensionality Reduction: using PCA, clustering, factor analysis etc

Discrete Data

Encoding: since some ML algorithms cannot work on categorical data, we need to turn categorical data into numerical data or vectors
Ordinal Values: convert each distinct feature into a random number (e.g. [r,g,b] becomes [1,2,3])
One-Hot Encoding: each of the m features becomes a vector of length m with containing only one 1 (e.g. [r, g, b] becomes [[1,0,0],[0,1,0],[0,0,1]])
Feature Hashing Scheme: turns arbitrary features into indices in a vector or matrix
Embeddings: if using words, convert words to vectors (word embeddings)

Statistical Analysis

Process of statistical reasoning: there is an underlying population of possible things we can potentially observe and only a small subset of them are actually sampled (ideally at random). Probability theory describes what properties our sample should have given the properties of the population, but ***statistical inference*** allows us to deduce what the full population is like after analyzing the sample.



Sampling From Distributions

Inverse Transform Sampling Sampling points from a given probability distribution is sometimes necessary to run simulations or whether your data fits a particular distribution. The general technique is called *inverse transform sampling* or Smirnov transform. First draw a random number p between [0,1]. Compute value x such that the CDF equals p: $F_X(x) = p$. Use x as the value to be the random value drawn from the distribution described by $F_X(x)$.

Monte Carlo Sampling In higher dimensions, correctly sampling from a given distribution becomes more tricky. Generally want to use Monte Carlo methods, which typically follow these rules: define a domain of possible inputs, generate random inputs from a probability distribution over the domain, perform a deterministic calculation, and analyze the results.

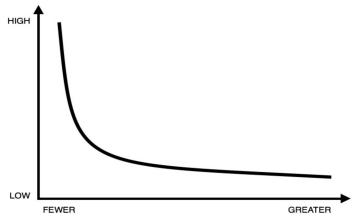
Classic Statistical Distributions

Binomial Distribution (Discrete)
Assume X is distributed Bin(n,p). X is the number of "successes" that we will achieve in n independent trials, where each trial is either a success or failure and each success occurs with the same probability p and each failure occurs with probability q=1-p.
PDF: $P(X = x) = \binom{n}{k} p^x (1-p)^{n-x}$
EV: $\mu = np$ Variance = npq

Normal/Gaussian Distribution (Continuous)
Assume X in distributed $\mathcal{N}(\mu, \sigma^2)$. It is a bell-shaped and symmetric distribution. Bulk of the values lie close to the mean and no value is too extreme. Generalization of the binomial distribution as n $\to \infty$.
PDF: $P(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/2\sigma^2}$
EV: μ Variance: σ^2
Implications: 68%-95%-99% rule. 68% of probability mass fall within 1σ of the mean, 95% within 2σ, and 99.7% within 3σ.

Poisson Distribution (Discrete)
Assume X is distributed Pois(λ). Poisson expresses the probability of a given number of events occurring in a fixed interval of time/space if these events occur independently and with a known constant rate λ.
PDF: $P(x) = \frac{e^{-\lambda}\lambda^x}{x!}$ EV: λ Variance = λ

Power Law Distributions (Discrete)
Many data distributions have much longer tails than the normal or Poisson distributions. In other words, the change in one quantity varies as a *power* of another quantity. It helps measure the inequality in the world. e.g. wealth, word frequency and Pareto Principle (80/20 Rule)
PDF: P(X=x) = $cx^{-\alpha}$, where α is the law's exponent and c is the normalizing constant



Modeling- Overview

Modeling is the process of incorporating information into a tool which can forecast and make predictions. Usually, we are dealing with statistical modeling where we want to analyze relationships between variables. Formally, we want to estimate a function $f(X)$ such that:

$$Y = f(X) + \epsilon$$

where X = $(X_1, X_2, ...X_p)$ represents the input variables, Y represents the output variable, and ϵ represents random error.

Statistical learning is set of approaches for estimating this $f(X)$.

Why Estimate f(X)?

Prediction: once we have a good estimate $\hat{f}(X)$, we can use it to make predictions on new data. We treat $\hat{f}$ as a black box, since we only care about the accuracy of the predictions, not why or how it works.
Inference: we want to understand the relationship between X and Y. We can no longer treat $\hat{f}$ as a black box since we want to understand how Y changes with respect to X = $(X_1, X_2, ...X_p)$

More About ϵ

The error term ϵ is composed of the reducible and irreducible error, which will prevent us from ever obtaining a perfect $\hat{f}$ estimate.

- **Reducible**: error that can potentially be reduced by using the most appropriate statistical learning technique to estimate f. The goal is to minimize the reducible error.
- **Irreducible**: error that cannot be reduced no matter how well we estimate f. Irreducible error is unknown and unmeasurable and will always be an upper bound for ϵ.

Note: There will always be trade-offs between model flexibility (prediction) and model interpretability (inference). This is just another case of the bias-variance trade-off. Typically, as flexibility increases, interpretability decreases. Much of statistical learning/modeling is finding a way to balance the two.

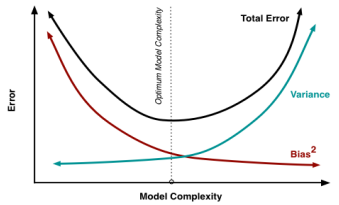
Modeling- Philosophies

Modeling is the process of incorporating information into a tool which can forecast and make predictions. Designing and validating models is important, as well as evaluating the performance of models. Note that the best forecasting model may not be the most accurate one.

Philosophies of Modeling

Occam's Razor Philosophical principle that the simplest explanation is the best explanation. In modeling, if we are given two models that predicts equally well, we should choose the simpler one. Choosing the more complex one can often result in overfitting.
Bias Variance Trade-Off Inherent part of predictive modeling, where models with lower bias will have higher variance and vice versa. Goal is to achieve low bias and low variance.

- ***Bias***: error from incorrect assumptions to make target function easier to learn (high bias $\to$ missing relevant relations or underfitting)
- ***Variance***: error from sensitivity to fluctuations in the dataset, or how much the target estimate would differ if different training data was used (high variance $\to$ modeling noise or overfitting)



No Free Lunch Theorem No single machine learning algorithm is better than all the others on all problems. It is common to try multiple models and find one that works best for a particular problem.

Thinking Like Nate Silver

1. Think Probabilistically Probabilistic forecasts are more meaningful than concrete statements and should be reported as probability distributions (including σ along with mean prediction μ.
2. Incorporate New Information Use live models, which continually updates using new information. To update, use Bayesian reasoning to calculate how probabilities change in response to new evidence.
3. Look For Consensus Forecast Use multiple distinct sources of evidence. Ssome models operate this way, such as boosting and bagging, which uses large number of weak classifiers to produce a strong one.

Modeling- Taxonomy

There are many different types of models. It is important to understand the trade-offs and when to use a certain type of model.

Parametric vs. Nonparametric

- **Parametric**: models that first make an assumption about a function form, or shape, of f (linear). Then fits the model. This reduces estimating f to just estimating set of parameters, but if our assumption was wrong, will lead to bad results.
- **Non-Parametric**: models that don't make any assumptions about f, which allows them to fit a wider range of shapes; but may lead to overfitting

Supervised vs. Unsupervised

- **Supervised**: models that fit input variables $x_i = (x_1, x_2, ...x_n)$ to a known output variables $y_i = (y_1, y_2, ...y_n)$
- **Unsupervised**: models that take in input variables $x_i = (x_1, x_2, ...x_n)$, but they do not have an associated output to supervise the training. The goal is understand relationships between the variables or observations.

Blackbox vs. Descriptive

- **Blackbox**: models that make decisions, but we do not know what happens "under the hood" e.g. deep learning, neural networks
- **Descriptive**: models that provide insight into *why* they make their decisions e.g. linear regression, decision trees

First-Principle vs. Data-Driven

- **First-Principle**: models based on a prior belief of how the system under investigation works, incorporates domain knowledge (ad-hoc)
- **Data-Driven**: models based on observed correlations between input and output variables

Deterministic vs. Stochastic

- **Deterministic**: models that produce a single "prediction" e.g. yes or no, true or false
- **Stochastic**: models that produce probability distributions over possible events

Flat vs. Hierarchical

- **Flat**: models that solve problems on a single level, no notion of subproblems
- **Hierarchical**: models that solve several different nested subproblems

Modeling- Evaluation Metrics

Need to determine how good our model is. Best way to assess models is out-of-sample predictions (data points your model has never seen).

Classification

	Predicted Yes	Predicted No
Actual Yes	True Positives (TP)	False Negatives (FN)
Actual No	False Positives (FP)	True Negatives (TN)

Accuracy: ratio of correct predictions over total predictions. Misleading when class sizes are substantially different. $accuracy = \frac{TP+TN}{TP+TN+FN+FP}$
Precision: how often the classifier is correct when it predicts positive: $precision = \frac{TP}{TP+FP}$
Recall: how often the classifier is correct for all positive instances: $recall = \frac{TP}{TP+FN}$
F-Score: single measurement to describe performance: $\mathrm{F} = 2 \cdot \frac{\mathrm{precision} \cdot \mathrm{recall}}{\mathrm{precision} + \mathrm{recall}}$
ROC Curves: plots true positive rates and false positive rates for various thresholds, or where the model determines if a data point is positive or negative (e.g. if >0.8, classify as positive). Best possible area under the ROC curve (AUC) is 1, while random is 0.5, or the main diagonal line.

Regression

Errors are defined as the difference between a prediction y′ and the actual result y.
Absolute Error: $\Delta = y\prime - y$
Squared Error: $\Delta^2 = (y\prime - y)^2$
Mean-Squared Error: $MSE = \frac{1}{n}\sum_{i=1}^{n}(y\prime_i - y_i)^2$
Root Mean-Squared Error: RMSD $= \sqrt{MSE}$
Absolute Error Distribution: Plot absolute error distribution: should be symmetric, centered around 0, bell-shaped, and contain rare extreme outliers.

Modeling- Evaluation Environment

Evaluation metrics provides use with the tools to estimate errors, but what should be the process to obtain the best estimate? Resampling involves repeatedly drawing samples from a training set and refitting a model to each sample, which provides us with additional information compared to fitting the model once, such as obtaining a better estimate for the test error.

Key Concepts

Training Data: data used to fit your models or the set used for learning
Validation Data: data used to tune the parameters of a model
Test Data: data used to evaluate how good your model is. Ideally your model should never touch this data until final testing/evaluation

Cross Validation

Class of methods that estimate test error by holding out a subset of training data from the fitting process.
Validation Set: split data into training set and validation set. Train model on training and estimate test error using validation. e.g. 80-20 split
Leave-One-Out CV (LOOCV): split data into training set and validation set, but the validation set consists of 1 observation. Then repeat n-1 times until all observations have been used as validation. Test erro is the average of these n test error estimates.
k-Fold CV: randomly divide data into k groups (folds) of approximately equal size. First fold is used as validation and the rest as training. Then repeat k times and find average of the k estimates.

Bootstrapping

Methods that rely on random sampling with replacement. Bootstrapping helps with quantifying uncertainty associated with a given estimate or model.

Amplifying Small Data Sets

What can we do it we don't have enough data?

- **Create Negative Examples**- e.g. classifying presidential candidates, most people would be unqualified so label most as unqualified
- **Synthetic Data**- create additional data by adding noise to the real data

Linear Regression

Linear regression is a simple and useful tool for predicting a quantitative response. The relationship between input variables $X = (X_1, X_2, ...X_p)$ and output variable Y takes the form:

$$Y \approx \beta_0 + \beta_1 X_1 + ... + \beta_p X_p + \epsilon$$

$\beta_0 ... \beta_p$ are the unknown coefficients (parameters) which we are trying to determine. The best coefficients will lead us to the best "fit", which can be found by minimizing the *residual sum squares* (RSS), or the sum of the differences between the actual ith value and the predicted ith value. $\text{RSS} = \sum_{i=1}^{n} e_i$, where $e_i = y_i - \hat{y}_i$

How to find best fit?

Matrix Form: We can solve the closed-form equation for coefficient vector w: $w = (X^T X)^{-1} X^T Y$. X represents the input data and Y represents the output data. This method is used for smaller matrices, since inverting a matrix is computationally expensive.

Gradient Descent: First-order optimization algorithm. We can find the minimum of a *convex* function by starting at an arbitrary point and repeatedly take steps in the downward direction, which can be found by taking the negative direction of the gradient. After several iterations, we will eventually converge to the minimum. In our case, the minimum corresponds to the coefficients with the minimum error, or the best line of fit. The learning rate α determines the size of the steps we take in the downward direction.

Gradient descent algorithm in two dimensions. Repeat until convergence.

1. $w_0^{t+1} := w_0^t - \alpha \frac{\partial}{\partial w_0} J(w_0, w_1)$
2. $w_1^{t+1} := w_1^t - \alpha \frac{\partial}{\partial w_1} J(w_0, w_1)$

For non-convex functions, gradient descent no longer guarantees an optimal solutions since there may be local minimas. Instead, we should run the algorithm from different starting points and use the best local minima we find for the solution.

Stochastic Gradient Descent: instead of taking a step after sampling the *entire* training set, we take a small batch of training data at random to determine our next step. Computationally more efficient and may lead to faster convergence.

Linear Regression II

Improving Linear Regression

Subset/Feature Selection: approach involves identifying a subset of the p predictors that we believe to be best related to the response. Then we fit model using the reduced set of variables.

- Best, Forward, and Backward Subset Selection

Shrinkage/Regularization: all variables are used, but estimated coefficients are shrunken towards zero relative to the least squares estimate. λ represents the tuning parameter- as λ increases, flexibility decreases $\rightarrow$ decreased variance but increased bias. The tuning parameter is key in determining the sweet spot between under and over-fitting. In addition, while Ridge will always produce a model with p variables, Lasso can force coefficients to be equal to zero.

- Lasso (L1): min RSS $+ \lambda \sum_{j=1}^{p} |\beta_j|$
- Ridge (L2): min RSS $+ \lambda \sum_{j=1}^{p} \beta_j^2$

Dimension Reduction: projecting p predictors into a M-dimensional subspace, where $M < p$. This is achieved by computing M different linear combinations of the variables. Can use PCA.

Miscellaneous: Removing outliers, feature scaling, removing multicollinearity (correlated variables)

Evaluating Model Accuracy

Residual Standard Error (RSE): $\text{RSE} = \sqrt{\frac{1}{n-2} RSS}$. Generally, the smaller the better.

R^2: Measure of fit that represents the proportion of variance explained, or the *variability in Y that can be explained using X*. It takes on a value between 0 and 1. Generally the higher the better. $R^2 = 1 - \frac{RSS}{TSS}$, where Total Sum of Squares (TSS) $= \sum (y_i - \bar{y})^2$

Evaluating Coefficient Estimates

Standard Error (SE) of the coefficients can be used to perform hypothesis tests on the coefficients:

H_0: No relationship between X and Y, H_a: Some relationship exists. A p-value can be obtained and can be interpreted as follows: a small p-value indicates that a relationship between the predictor (X) and the response (Y) exists. Typical p-value cutoffs are around 5 or 1 %.

Logistic Regression

Logistic regression is used for classification, where the response variable is categorical rather than numerical.

The model works by predicting the probability that Y belongs to a particular category by first fitting the data to a linear regression model, which is then passed to the logistic function (below). The logistic function will always produce a S-shaped curve, so regardless of X, we can always obtain a sensible answer (between 0 and 1). If the probability is above a certain predetermined threshold (e.g. P(Yes) > 0.5), then the model will predict Yes.

$$p(X) = \frac{e^{\beta_0 + \beta_1 X_1 + ... + \beta_p X_p}}{1 + e^{\beta_0 + \beta_1 X_1 + ... + \beta_p X_p}}$$

How to find best coefficients?

Maximum Likelihood: The coefficients $\beta_0 ... \beta_p$ are unknown and must be estimated from the training data. We seek estimates for $\beta_0 ... \beta_p$ such that the predicted probability $\hat{p}(x_i)$ of each observation is a number close to one if its observed in a certain class and close to zero otherwise. This is done by maximizing the likelihood function:

$$l(\beta_0, \beta_1) = \prod_{i:y_i=1} p(x_i) \prod_{i':y_{i'}=1} (1 - p(x_i))$$

Potential Issues

Imbalanced Classes: imbalance in classes in training data lead to poor classifiers. It can result in a lot of false positives and also lead to few training data. Solutions include forcing balanced data by removing observations from the larger class, replicate data from the smaller class, or heavily weigh the training examples toward instances of the larger class.

Multi-Class Classification: the more classes you try to predict, the harder it will be for the the classifier to be effective. It is possible with logistic regression, but another approach, such as Linear Discriminant Analysis (LDA), may prove better.

Distance/Network Methods

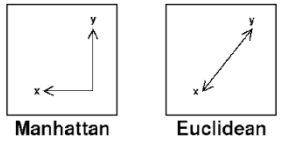
Interpreting examples as points in space provides a way to find natural groupings or clusters among data e.g. which stars are the closest to our sun? Networks can also be built from point sets (vertices) by connecting related points.

Measuring Distances/Similarity Measure

There are several ways of measuring distances between points a and b in d dimensions- with closer distances implying similarity.

Minkowski Distance Metric: $d_k(a,b) = \sqrt[k]{\sum_{i=1}^{d} |a_i - b_i|^k}$
The parameter k provides a way to tradeoff between the largest and the total dimensional difference. In other words, larger values of k place more emphasis on large differences between feature values than smaller values. Selecting the right k can significantly impact the the meaningfulness of your distance function. The most popular values are 1 and 2.

- Manhattan (k=1): city block distance, or the sum of the absolute difference between two points
- Euclidean (k=2): straight line distance



Manhattan Euclidean

Weighted Minkowski: $d_k(a,b) = \sqrt[k]{\sum_{i=1}^{d} w_i |a_i - b_i|^k}$, in some scenarios, not all dimensions are equal. Can convey this idea using w_i. Generally not a good idea- should normalize data by Z-scores before computing distances.

Cosine Similarity: $cos(a,b) = \frac{a \cdot b}{|a||b|}$, calculates the similarity between 2 non-zero vectors, where $a \cdot b$ is the dot product (normalized between 0 and 1), higher values imply more similar vectors

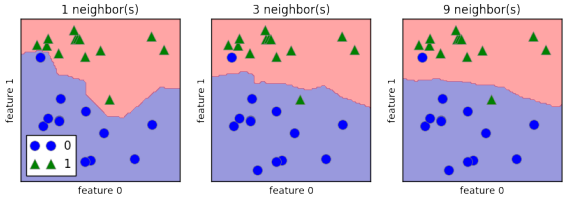
Kullback-Leibler Divergence: $KL(A||B) = \sum_{i=i}^{d} a_i log_2 \frac{a_i}{b_i}$
KL divergence measures the distances between probability distributions by measuring the uncertainty gained or uncertainty lost when replacing distribution A with distribution B. However, this is not a metric but forms the basis for the Jensen-Shannon Divergence Metric.
Jensen-Shannon: $JS(A,B) = \frac{1}{2}KL(A||M) + \frac{1}{2}KL(M||B)$, where M is the average of A and B. The JS function is the right metric for calculating distances between probability distributions

Nearest Neighbor Classification

Distance functions allow us to identify the points closest to a given target, or the *nearest neighbors (NN)* to a given point. The advantages of NN include simplicity, interpretability and non-linearity.

k-Nearest Neighbors

Given a positive integer k and a point x_0, the KNN classifier first identifies k points in the training data most similar to x_0, then estimates the conditional probability of x_0 being in class j as the fraction of the k points whose values belong to j. The optimal value for k can be found using cross validation.



KNN Algorithm

1. Compute distance D(a,b) from point b to all points
2. Select k closest points and their labels
3. Output class with most frequent labels in k points

Optimizing KNN

Comparing a query point a in d dimensions against n training examples computes with a runtime of $O(nd)$, which can cause lag as points reach millions or billions. Popular choices to speed up KNN include:

- **Vernoi Diagrams**: partitioning plane into regions based on distance to points in a specific subset of the plane
- **Grid Indexes**: carve up space into d-dimensional boxes or grids and calculate the NN in the same cell as the point
- **Locality Sensitive Hashing (LSH)**: abandons the idea of finding the exact nearest neighbors. Instead, batch up nearby points to quickly find the most appropriate bucket B for our query point. LSH is defined by a hash function $h(p)$ that takes a point/vector as input and produces a number/ code as output, such that it is likely that h(a) = h(b) if a and b are close to each other, and h(a)!= h(b) if they are far apart.

Clustering

Clustering is the problem of grouping points by similarity using distance metrics, which ideally reflect the similarities you are looking for. Often items come from logical "sources" and clustering is a good way to reveal those origins. Perhaps the first thing to do with any data set. Possible applications include: hypothesis development, modeling over smaller subsets of data, data reduction, outlier detection.

K-Means Clustering

Simple and elegant algorithm to partition a dataset into K distinct, non-overlapping clusters.

1. Choose a K. Randomly assign a number between 1 and K to each observation. These serve as initial cluster assignments
2. Iterate until cluster assignments stop changing
   (a) For each of the K clusters, compute the cluster centroid. The kth cluster centroid is the vector of the p feature means for the observations in the kth cluster.
   (b) Assign each observation to the cluster whose centroid is closest (where closest is defined using distance metric).

Since the results of the algorithm depends on the initial random assignments, it is a good idea to repeat the algorithm from different random initializations to obtain the best overall results. Can use MSE to determine which cluster assignment is better.

Hierarchical Clustering

Alternative clustering algorithm that does not require us to commit to a particular K. Another advantage is that it results in a nice visualization called a **dendrogram**. Observations that fuse at bottom are similar, where those at the top are quite different- we draw conclusions based on the location on the vertical rather than horizontal axis.

1. Begin with n observations and a measure of all the $\frac{(n)n-1}{2}$ pairwise dissimilarities. Treat each observation as its own cluster.
2. For i = n, n-1, ...2
   (a) Examine all pairwise inter-cluster dissimilarities among the i clusters and identify the pair of clusters that are least dissimilar (most similar). Fuse these two clusters. The dissimilarity between these two clusters indicates height in dendrogram where fusion should be placed.
   (b) Assign each observation to the cluster whose centroid is closest (where closest is defined using distance metric).

Linkage: Complete (max dissimilarity), Single (min), Average, Centroid (between centroids of cluster A and B)

Machine Learning Part I

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 overfitting.

Interpretability: 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

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

Naive Bayes

Naive Bayes methods are a set of supervised learning algorithms based on applying Bayes' theorem with the "naive" assumption of independence between every pair of features.

Problem: Suppose we need to classify vector $X = x_1...x_n$ into m classes, $C_1...C_m$. We need to compute the probability of each possible class given X, so we can assign X the label of the class with highest probability. We can calculate a probability using the Bayes' Theorem:

$$P(C_i|X) = \frac{P(X|C_i)P(C_i)}{P(X)}$$

Where:

1. $P(C_i)$: the prior probability of belonging to class i
2. $P(X)$: normalizing constant, or probability of seeing the given input vector over all possible input vectors
3. $P(X|C_i)$: the conditional probability of seeing input vector X given we know the class is C_i

The prediction model will formally look like:

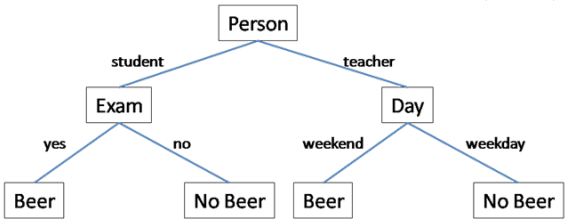
$$C(X) = argmax_{i \in classes(t)} \frac{P(X|C_i)P(C_i)}{P(X)}$$

where C(X) is the prediction returned for input X.

Machine Learning Part II

Decision Trees

Binary branching structure used to classify an arbitrary input vector X. Each node in the tree contains a simple feature comparison against some field ($x_i > 42$?). Result of each comparison is either true or false, which determines if we should proceed along to the left or right child of the given node. Also known as sometimes called classification and regression trees (CART).



Advantages: Non-linearity, support for categorical variables, easy to interpret, application to regression.

Disadvantages: Prone to overfitting, instable (not robust to noise), high variance, low bias

Note: rarely do models just use one decision tree. Instead, we aggregate many decision trees using methods like ensembling, bagging, and boosting.

Ensembles, Bagging, Random Forests, Boosting

Ensemble learning is the strategy of combining many different classifiers/models into one predictive model. It revolves around the idea of voting: a so-called "wisdom of crowds" approach. The most predicted class will be the final prediction.

Bagging: ensemble method that works by taking B bootstrapped subsamples of the training data and constructing B trees, each tree training on a distinct subsample as

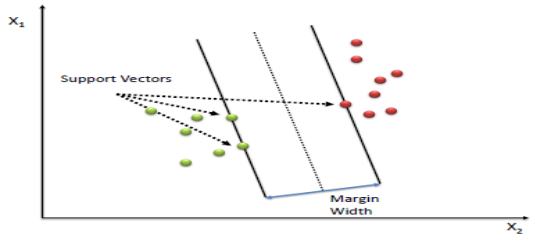
Random Forests: builds on bagging by decorrelating the trees. We do everything the same like in bagging, but when we build the trees, everytime we consider a split, a random sample of the p predictors is chosen as split candidates, not the full set (typically m $\approx \sqrt{p}$). When m = p, then we are just doing bagging.

Boosting: the main idea is to improve our model where it is not performing well by using information from previously constructed classifiers. Slow learner. Has 3 tuning parameters: number of classifiers B, learning parameter λ, interaction depth d (controls interaction order of model).

Machine Learning Part III

Support Vector Machines

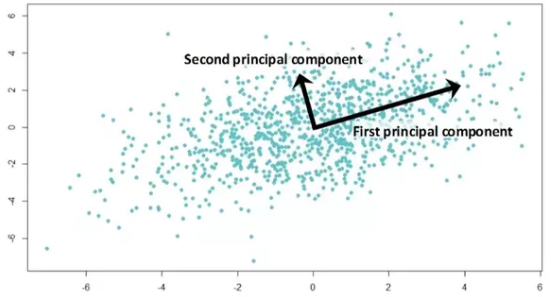
Work by constructing a hyperplane that separates points between two classes. The hyperplane is determined using the maximal margin hyperplane, which is the hyperplane that is the maximum distance from the training observations. This distance is called the margin. Points that fall on one side of the hyperplane are classified as -1 and the other +1.



Principal Component Analysis (PCA)

Principal components allow us to summarize a set of correlated variables with a smaller set of variables that collectively explain most of the variability in the original set. Essentially, we are "dropping" the least important feature variables.

Principal Component Analysis is the process by which principal components are calculated and the use of them to analyzing and understanding the data. PCA is an unsupervised approach and is used for dimensionality reduction, feature extraction, and data visualization. Variables after performing PCA are independent. Scaling variables is also important while performing PCA.



Machine Learning Part IV

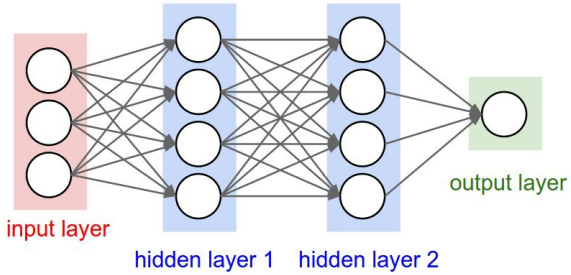
ML Terminology and Concepts

Features: input data/variables used by the ML model
Feature Engineering: transforming input features to be more useful for the models. e.g. mapping categories to buckets, normalizing between -1 and 1, removing null
Train/Eval/Test: training is data used to optimize the model, evaluation is used to asses the model on new data during training, test is used to provide the final result
Classification/Regression: regression is prediction a number (e.g. housing price), classification is prediction from a set of categories(e.g. predicting red/blue/green)
Linear Regression: predicts an output by multiplying and summing input features with weights and biases
Logistic Regression: similar to linear regression but predicts a probability
Overfitting: model performs great on the input data but poorly on the test data (combat by dropout, early stopping, or reduce # of nodes or layers)
Bias/Variance: how much output is determined by the features. more variance often can mean overfitting, more bias can mean a bad model
Regularization: variety of approaches to reduce overfitting, including adding the weights to the loss function, randomly dropping layers (dropout)
Ensemble Learning: training multiple models with different parameters to solve the same problem
A/B testing: statistical way of comparing 2+ techniques to determine which technique performs better and also if difference is statistically significant
Baseline Model: simple model/heuristic used as reference point for comparing how well a model is performing
Bias: prejudice or favoritism towards some things, people, or groups over others that can affect collection/sampling and interpretation of data, the design of a system, and how users interact with a system
Dynamic Model: model that is trained online in a continuously updating fashion
Static Model: model that is trained offline
Normalization: process of converting an actual range of values into a standard range of values, typically -1 to +1
Independently and Identically Distributed (i.i.d): data drawn from a distribution that doesn't change, and where each value drawn doesn't depend on previously drawn values; ideal but rarely found in real life
Hyperparameters: the "knobs" that you tweak during successive runs of training a model
Generalization: refers to a model's ability to make correct predictions on new, previously unseen data as opposed to the data used to train the model
Cross-Entropy: quantifies the difference between two probability distributions

Deep Learning Part I

What is Deep Learning?

Deep learning is a subset of machine learning. One popular DL technique is based on Neural Networks (NN), which loosely mimic the human brain and the code structures are arranged in layers. Each layer's input is the previous layer's output, which yields progressively higher-level features and defines a hierarchy. A Deep Neural Network is just a NN that has more than 1 hidden layer.



Recall that statistical learning is all about approximating $f(X)$. Neural networks are known as **universal approximators**, meaning no matter how complex a function is, there exists a NN that can (approximately) do the job. We can increase the approximation (or complexity) by adding more hidden layers and neurons.

Popular Architectures

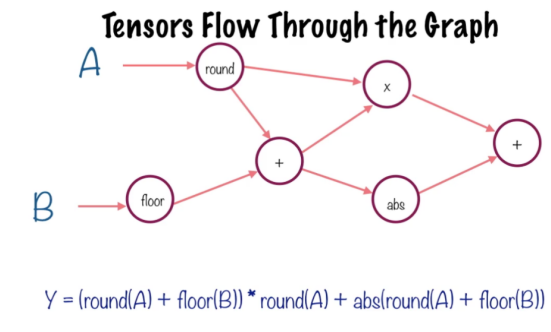
There are different kinds of NNs that are suitable for certain problems, which depend on the NN's architecture.

Linear Classifier: takes input features and combines them with weights and biases to predict output value
DNN: deep neural net, contains intermediate layers of nodes that represent "hidden features" and activation functions to represent non-linearity
CNN: convolutional NN, has a combination of convolutional, pooling, dense layers. popular for image classification.
Transfer Learning: use existing trained models as starting points and add additional layers for the specific use case. idea is that highly trained existing models know general features that serve as a good starting point for training a small network on specific examples
RNN: recurrent NN, designed for handling a sequence of inputs that have "memory" of the sequence. LSTMs are a fancy version of RNNs, popular for NLP
GAN: general adversarial NN, one model creates fake examples, and another model is served both fake example and real examples and is asked to distinguish
Wide and Deep: combines linear classifiers with deep neural net classifiers, "wide" linear parts represent memorizing specific examples and "deep" parts represent understanding high level features

Deep Learning Part II

Tensorflow

Tensorflow is an open source software library for numerical computation using data flow graphs. Everything in TF is a graph, where nodes represent operations on data and edges represent the data. Phase 1 of TF is building up a computation graph and phase 2 is executing it. It is also distributed, meaning it can run on either a cluster of machines or just a single machine.
TF is extremely popular/suitable for working with Neural Networks, since the way TF sets up the computational graph pretty much resembles a NN.



Tensors

In a graph, tensors are the edges and are multidimensional data arrays that flow through the graph. Central unit of data in TF and consists of a set of primitive values shaped into an array of any number of dimensions.
A tensor is characterized by its rank (# dimensions in tensor), shape (# of dimensions and size of each dimension), data type (data type of each element in tensor).

Placeholders and Variables

Variables: best way to represent shared, persistent state manipulated by your program. These are the parameters of the ML model are altered/trained during the training process. Training variables.
Placeholders: way to specify inputs into a graph that hold the place for a Tensor that will be fed at runtime. They are assigned once, do not change after. Input nodes

Deep Learning Part III

Deep Learning Terminology and Concepts

Neuron: node in a NN, typically taking in multiple input values and generating one output value, calculates the output value by applying an activation function (nonlinear transformation) to a weighted sum of input values
Weights: edges in a NN, the goal of training is to determine the optimal weight for each feature; if weight = 0, corresponding feature does not contribute
Neural Network: composed of neurons (simple building blocks that actually "learn"), contains activation functions that makes it possible to predict non-linear outputs
Activation Functions: mathematical functions that introduce non-linearity to a network e.g. RELU, tanh
Sigmoid Function: function that maps very negative numbers to a number very close to 0, huge numbers close to 1, and 0 to .5. Useful for predicting probabilities
Gradient Descent/Backpropagation: fundamental loss optimizer algorithms, of which the other optimizers are usually based. Backpropagation is similar to gradient descent but for neural nets
Optimizer: operation that changes the weights and biases to reduce loss e.g. Adagrad or Adam
Weights / Biases: weights are values that the input features are multiplied by to predict an output value. Biases are the value of the output given a weight of 0.
Converge: algorithm that converges will eventually reach an optimal answer, even if very slowly. An algorithm that doesn't converge may never reach an optimal answer.
Learning Rate: rate at which optimizers change weights and biases. High learning rate generally trains faster but risks not converging, whereas a lower rate trains slower
Numerical Instability: issues with very large/small values due to limits of floating point numbers in computers
Embeddings: mapping from discrete objects, such as words, to vectors of real numbers. useful because classifiers/neural networks work well on vectors of real numbers
Convolutional Layer: series of convolutional operations, each acting on a different slice of the input matrix
Dropout: method for regularization in training NNs, works by removing a random selection of some units in a network layer for a single gradient step
Early Stopping: method for regularization that involves ending model training early
Gradient Descent: technique to minimize loss by computing the gradients of loss with respect to the model's parameters, conditioned on training data
Pooling: Reducing a matrix (or matrices) created by an earlier convolutional layer to a smaller matrix. Pooling usually involves taking either the maximum or average value across the pooled area

Big Data- Hadoop Overview

Data can no longer fit in memory on one machine (monolithic), so a new way of computing was devised using a group of computers to process this "big data" (distributed). Such a group is called a cluster, which makes up server farms. All of these servers have to be coordinated in the following ways: partition data, coordinate computing tasks, handle fault tolerance/recovery, and allocate capacity to process.

Hadoop

Hadoop is an open source *distributed* processing framework that manages data processing and storage for big data applications running in clustered systems. It is comprised of 3 main components:

- **Hadoop Distributed File System (HDFS)**: a distributed file system that provides high-throughput access to application data by partitioning data across many machines
- **YARN**: framework for job scheduling and cluster resource management (task coordination)
- **MapReduce**: YARN-based system for parallel processing of large data sets on multiple machines

HDFS

Each disk on a different machine in a cluster is comprised of 1 master node and the rest are workers/data nodes. The **master node** manages the overall file system by storing the directory structure and the metadata of the files. The **data nodes** physically store the data. Large files are broken up and distributed across multiple machines, which are also replicated across multiple machines to provide fault tolerance.

MapReduce

Parallel programming paradigm which allows for processing of huge amounts of data by running processes on multiple machines. Defining a MapReduce job requires two stages: map and reduce.

- **Map**: operation to be performed in parallel on small portions of the dataset. the output is a key-value pair $< K, V >$
- **Reduce**: operation to combine the results of Map

YARN- Yet Another Resource Negotiator

Coordinates tasks running on the cluster and assigns new nodes in case of failure. Comprised of 2 subcomponents: the resource manager and the node manager. The **resource manager** runs on a single master node and schedules tasks across nodes. The **node manager** runs on all other nodes and manages tasks on the individual node.

Big Data- Hadoop Ecosystem

An entire ecosystem of tools have emerged around Hadoop, which are based on interacting with HDFS. Below are some popular ones:

Hive: data warehouse software built o top of Hadoop that facilitates reading, writing, and managing large datasets residing in distributed storage using SQL-like queries (HiveQL). Hive abstracts away underlying MapReduce jobs and returns HDFS in the form of tables (not HDFS).
Pig: high level scripting language (Pig Latin) that enables writing complex data transformations. It pulls unstructured/incomplete data from sources, cleans it, and places it in a database/data warehouses. Pig performs ETL into data warehouse while Hive queries from data warehouse to perform analysis (GCP: DataFlow).
Spark: framework for writing fast, distributed programs for data processing and analysis. Spark solves similar problems as Hadoop MapReduce but with a fast in-memory approach. It is an unified engine that supports SQL queries, streaming data, machine learning and graph processing. Can operate separately from Hadoop but integrates well with Hadoop. Data is processed using Resilient Distributed Datasets (RDDs), which are immutable, lazily evaluated, and tracks lineage. ;
Hbase: non-relational, NoSQL, column-oriented database management system that runs on top of HDFS. Well suited for sparse data sets (GCP: BigTable)
Flink/Kafka: stream processing framework. Batch streaming is for bounded, finite datasets, with periodic updates, and delayed processing. Stream processing is for unbounded datasets, with continuous updates, and immediate processing. Stream data and stream processing must be decoupled via a message queue. Can group streaming data (windows) using tumbling (non-overlapping time), sliding (overlapping time), or session (session gap) windows.
Beam: programming model to define and execute data processing pipelines, including ETL, batch and stream (continuous) processing. After building the pipeline, it is executed by one of Beam's distributed processing back-ends (Apache Apex, Apache Flink, Apache Spark, and Google Cloud Dataflow). Modeled as a Directed Acyclic Graph (DAG).
Oozie: workflow scheduler system to manage Hadoop jobs
Sqoop: transferring framework to transfer large amounts of data into HDFS from relational databases (MySQL)

SQL Part I

Structured Query Language (SQL) is a declarative language used to access & manipulate data in databases. Usually the database is a Relational Database Management System (RDBMS), which stores data arranged in relational database tables. A table is arranged in columns and rows, where columns represent characteristics of stored data and rows represent actual data entries.

Basic Queries

- filter columns: **SELECT** col1, col3... **FROM** table1
- filter the rows: **WHERE** col4 = 1 **AND** col5 = 2
- aggregate the data: **GROUP BY**...
- limit aggregated data: **HAVING** count(*) > 1
- order of the results: **ORDER BY** col2

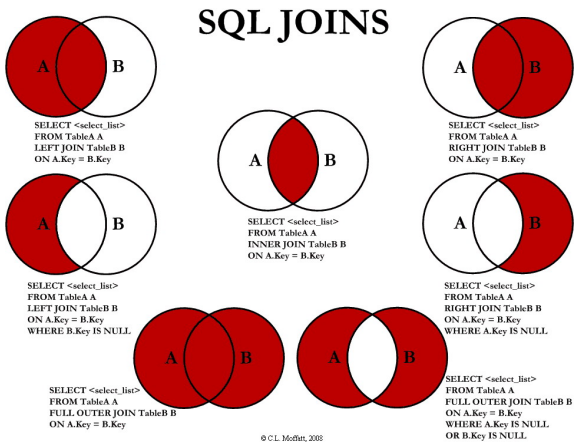
Useful Keywords for **SELECT**
DISTINCT- return unique results
BETWEEN a AND b- limit the range, the values can be numbers, text, or dates
LIKE- pattern search within the column text
IN (a, b, c) - check if the value is contained among given

Data Modification

- update specific data with the **WHERE** clause:
UPDATE table1 **SET** col1 = 1 **WHERE** col2 = 2
- insert values manually
INSERT INTO table1 (col1,col3) **VALUES** (val1,val3);
- by using the results of a query
INSERT INTO table1 (col1,col3) **SELECT** col,col2 FROM table2;

Joins

The JOIN clause is used to combine rows from two or more tables, based on a related column between them.



Python- Data Structures

Data structures are a way of storing and manipulating data and each data structure has its own strengths and weaknesses. Combined with algorithms, data structures allow us to efficiently solve problems. It is important to know the main types of data structures that you will need to efficiently solve problems.

Lists: or arrays, ordered sequences of objects, mutable

```
>>> l = [42, 3.14, "hello","world"]
```

Tuples: like lists, but immutable

```
>>> t = (42, 3.14, "hello","world")
```

Dictionaries: hash tables, key-value pairs, unsorted

```
>>> d = {"life": 42, "pi": 3.14}
```

Sets: mutable, unordered sequence of unique elements. frozensets are just immutable sets

```
>>> s = set([42, 3.14, "hello","world"])
```

Collections Module

deque: double-ended queue, generalization of stacks and queues; supports append, appendLeft, pop, rotate, etc

```
>>> s = deque([42, 3.14, "hello","world"])
```

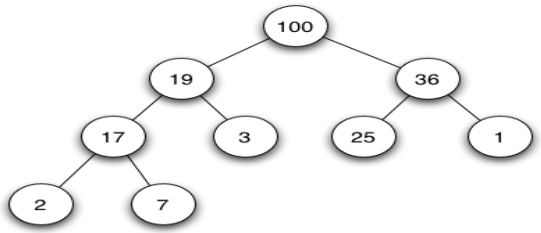
Counter: dict subclass, unordered collection where elements are stored as keys and counts stored as values

```
>>> c = Counter('apple')
>>> print(c)
Counter({'p': 2, 'a': 1, 'l': 1, 'e': 1})
```

heqpq Module

Heap Queue: priority queue, heaps are binary trees for which every parent node has a value greater than or equal to any of its children (max-heap), order is important; supports push, pop, pushpop, heapify, replace functionality

```
>>> heap = []
>>> for n in data:
...     heappush(heap, n)
>>> heap
[0, 1, 3, 6, 2, 8, 4, 7, 9, 5]
```



Recommended Resources

- Data Science Design Manual (`www.springer.com/us/book/9783319554433`)
- Introduction to Statistical Learning (`www-bcf.usc.edu/~gareth/ISL/`)
- Probability Cheatsheet (`/www.wzchen.com/probability-cheatsheet/`)
- Google's Machine Learning Crash Course (`developers.google.com/machine-learning/crash-course/`)

DataCamp

Data Science Cheat Sheet for Business Leaders

Data Science Basics

Types of Data Science

→ **Descriptive Analytics (Business Intelligence)**: Get useful data in front of the right people in the form of dashboards, reports, and emails

- Which customers have churned?
- Which homes have sold in a given location, and do homes of a certain size sell more quickly?

→ **Predictive Analytics (Machine Learning):** Put data science models continuously into production

- Which customers may churn?
- How much will a home sell for, given its location and number of rooms?

→ **Prescriptive Analytics (Decision Science):** Use data to help a company make decisions

- What should we do about the particular types of customers that are prone to churn?
- How should we market a home to sell quickly, given its location and number of rooms?

The Standard Data Science Workflow

1. **Data Collection:** Compile data from different sources and store it for efficient access

↓

2. **Exploration and Visualization:** Explore and visualize data through dashboards

↓

3. **Experimentation and Prediction:** The buzziest topic in data science—machine learning!

Building a Data Science Team

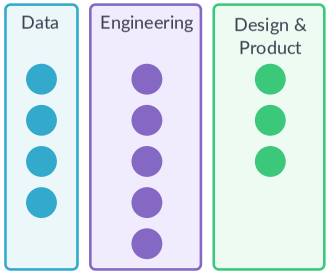
Your data team members require different skills for different purposes.

Data Engineer	Data Analyst	Machine Learning Engineer	Data Scientist
Store and maintain data	Visualize and describe data	Write production-level code to predict with data	Build custom models to drive business decisions
SQL/Java/Scala/Python	SQL + BI Tools + Spreadsheets	Python/Java/R	Python/R/SQL

Data Science Team Organizational Models

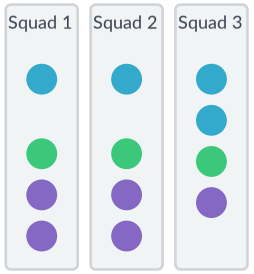
Centralized/isolated

The data team is the owner of data and answers requests from other teams



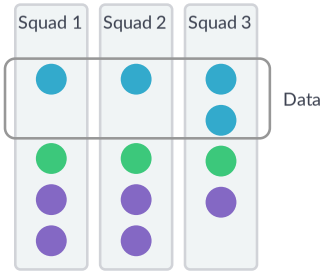
Embedded

Data experts are dispersed across an organization and report to functional leaders



Hybrid

Data experts sit with functional teams and also report to the Chief Data Scientist—so data is an organizational priority



datacamp.com/courses/data-science-for-business-leaders

datacamp.com/business

Python For Data Science *Cheat Sheet*

Python Basics

Learn More Python for Data Science Interactively at www.datacamp.com

Variables and Data Types

Variable Assignment

```
>>> x=5
>>> x
 5
```

Calculations With Variables

```
>>> x+2
 7
>>> x-2
 3
>>> x*2
 10
>>> x**2
 25
>>> x%2
 1
>>> x/float(2)
 2.5
```

Sum of two variables

Subtraction of two variables

Multiplication of two variables

Exponentiation of a variable

Remainder of a variable

Division of a variable

Types and Type Conversion

`str()`	`'5', '3.45', 'True'`	Variables to strings
`int()`	`5, 3, 1`	Variables to integers
`float()`	`5.0, 1.0`	Variables to floats
`bool()`	`True, True, True`	Variables to booleans

Asking For Help

```
>>> help(str)
```

Lists

Also see NumPy Arrays

```
>>> a = 'is'
>>> b = 'nice'
>>> my_list = ['my', 'list', a, b]
>>> my_list2 = [[4,5,6,7], [3,4,5,6]]
```

Selecting List Elements

Index starts at 0

Subset

```
>>> my_list[1]
>>> my_list[-3]
```

Select item at index 1

Select 3rd last item

Slice

```
>>> my_list[1:3]
>>> my_list[1:]
>>> my_list[:3]
>>> my_list[:]
```

Select items at index 1 and 2

Select items after index 0

Select items before index 3

Copy my_list

Subset Lists of Lists

```
>>> my_list2[1][0]
>>> my_list2[1][:2]
```

my_list[list][itemOfList]

List Operations

```
>>> my_list + my_list
['my', 'list', 'is', 'nice', 'my', 'list', 'is', 'nice']
>>> my_list * 2
['my', 'list', 'is', 'nice', 'my', 'list', 'is', 'nice']
>>> my_list2 > 4
True
```

List Methods

`>>> my_list.index(a)`	Get the index of an item
`>>> my_list.count(a)`	Count an item
`>>> my_list.append('!')`	Append an item at a time
`>>> my_list.remove('!')`	Remove an item
`>>> del(my_list[0:1])`	Remove an item
`>>> my_list.reverse()`	Reverse the list
`>>> my_list.extend('!')`	Append an item
`>>> my_list.pop(-1)`	Remove an item
`>>> my_list.insert(0,'!')`	Insert an item
`>>> my_list.sort()`	Sort the list

Strings

```
>>> my_string = 'thisStringIsAwesome'
>>> my_string
'thisStringIsAwesome'
```

String Operations

```
>>> my_string * 2
 'thisStringIsAwesomethisStringIsAwesome'
>>> my_string + 'Innit'
 'thisStringIsAwesomeInnit'
>>> 'm' in my_string
 True
```

String Operations

Index starts at 0

```
>>> my_string[3]
>>> my_string[4:9]
```

String Methods

`>>> my_string.upper()`	String to uppercase
`>>> my_string.lower()`	String to lowercase
`>>> my_string.count('w')`	Count String elements
`>>> my_string.replace('e', 'i')`	Replace String elements
`>>> my_string.strip()`	Strip whitespaces

Libraries

Import libraries

```
>>> import numpy
>>> import numpy as np
```

Selective import

```
>>> from math import pi
```

pandas — Data analysis

Machine learning

NumPy — Scientific computing

matplotlib — 2D plotting

Install Python

ANACONDA — Leading open data science platform powered by Python

spyder — Free IDE that is included with Anaconda

jupyter — Create and share documents with live code, visualizations, text, ...

Numpy Arrays

Also see Lists

```
>>> my_list = [1, 2, 3, 4]
>>> my_array = np.array(my_list)
>>> my_2darray = np.array([[1,2,3],[4,5,6]])
```

Selecting Numpy Array Elements

Index starts at 0

Subset

```
>>> my_array[1]
  2
```

Select item at index 1

Slice

```
>>> my_array[0:2]
  array([1, 2])
```

Select items at index 0 and 1

Subset 2D Numpy arrays

```
>>> my_2darray[:,0]
  array([1, 4])
```

my_2darray[rows, columns]

Numpy Array Operations

```
>>> my_array > 3
 array([False, False, False,  True], dtype=bool)
>>> my_array * 2
  array([2, 4, 6, 8])
>>> my_array + np.array([5, 6, 7, 8])
 array([6, 8, 10, 12])
```

Numpy Array Functions

`>>> my_array.shape`	Get the dimensions of the array
`>>> np.append(other_array)`	Append items to an array
`>>> np.insert(my_array, 1, 5)`	Insert items in an array
`>>> np.delete(my_array,[1])`	Delete items in an array
`>>> np.mean(my_array)`	Mean of the array
`>>> np.median(my_array)`	Median of the array
`>>> my_array.corrcoef()`	Correlation coefficient
`>>> np.std(my_array)`	Standard deviation

Mémento v2.0.6

Python 3 Cheat Sheet

Latest version on :
https://perso.limsi.fr/pointal/python:memento

Base Types

integer, float, boolean, string, bytes

```
int 783  0 -192  0b010 0o642 0xF3
                 zero  binary octal hexa
float 9.23 0.0  -1.7e-6
                        ×10^-6
bool True False
str "One\nTwo"        Multiline string:
    escaped new line    """X\tY\tZ
      'I\'m'            1\t2\t3"""
    escaped '           escaped tab
bytes b"toto\xfe\775"
          hexadecimal octal
```

immutables

Container Types

- **ordered sequences**, fast index access, repeatable values

```
list [1,5,9]   ["x",11,8.9]   ["mot"]   []
tuple (1,5,9)  11,"y",7.4     ("mot",)  ()
```

Non modifiable values (immutables) — *expression with only comas →* `tuple`

```
str bytes  (ordered sequences of chars / bytes)   ""  b""
```

- **key containers**, no *a priori* order, fast key access, each key is unique

```
dictionary  dict {"key":"value"}   dict(a=3,b=4,k="v")   {}
(key/value associations) {1:"one",3:"three",2:"two",3.14:"π"}
collection  set {"key1","key2"}    {1,9,3,0}            set()
```

keys=hashable values (base types, immutables…) `frozenset` *immutable set* *empty*

Identifiers

for variables, functions, modules, classes… names

`a…zA…Z_` followed by `a…zA…Z_0…9`

- diacritics allowed but should be avoided
- language keywords forbidden
- lower/UPPER case discrimination

☺ `a toto x7 y_max BigOne`
☹ `0y and for`

Variables assignment

`=`

assignment ⇔ **binding** of a *name* with a *value*

1) *evaluation of right side expression value*
2) *assignment in order with left side names*

```
x=1.2+8+sin(y)
a=b=c=0          assignment to same value
y,z,r=9.2,-7.6,0 multiple assignments
a,b=b,a          values swap
a,*b=seq  }
*a,b=seq  } unpacking of sequence in item and list
x+=3   increment ⇔ x=x+3      and *= /= %= …
x-=2   decrement ⇔ x=x-2
x=None « undefined » constant value
del x  remove name x
```

Conversions

`type(`*expression*`)`

```
int("15") → 15
int("3f",16) → 63        can specify integer number base in 2nd parameter
int(15.56) → 15          truncate decimal part
float("-11.24e8") → -1124000000.0
round(15.56,1)→15.6      rounding to 1 decimal (0 decimal → integer number)
bool(x)  False for null x, empty container x , None or False x ; True for other x
str(x)→ "…"              representation string of x for display (cf. formatting on the back)
chr(64)→'@'  ord('@')→64   code ↔ char
repr(x)→ "…"             literal representation string of x
bytes([72,9,64]) → b'H\t@'
list("abc") → ['a','b','c']
dict([(3,"three"),(1,"one")]) → {1:'one',3:'three'}
set(["one","two"]) → {'one','two'}
separator str and sequence of str → assembled str
  ':'.join(['toto','12','pswd']) → 'toto:12:pswd'
str splitted on whitespaces → list of str
  "words with  spaces".split() → ['words','with','spaces']
str splitted on separator str → list of str
  "1,4,8,2".split(",") → ['1','4','8','2']
sequence of one type → list of another type (via list comprehension)
  [int(x) for x in ('1','29','-3')] → [1,29,-3]
```

Sequence Containers Indexing

for lists, tuples, strings, bytes…

negative index	−5	−4	−3	−2	−1
positive index	0	1	2	3	4
`lst=`	[10,	20,	30,	40,	50]
positive slice	0	1	2	3	4	5
negative slice	−5	−4	−3	−2	−1	

Items count

`len(lst)→5`

index from 0
(here from 0 to 4)

Individual access to **items** via `lst[`*index*`]`

```
lst[0]→10   ⇒ first one      lst[1]→20
lst[-1]→50  ⇒ last one       lst[-2]→40
```

On mutable sequences (`list`), remove with `del lst[3]` *and modify with assignment* `lst[4]=25`

Access to **sub-sequences** via `lst[`*start slice*`:`*end slice*`:`*step*`]`

```
lst[:-1]→[10,20,30,40]   lst[::-1]→[50,40,30,20,10]   lst[1:3]→[20,30]   lst[:3]→[10,20,30]
lst[1:-1]→[20,30,40]     lst[::-2]→[50,30,10]         lst[-3:-1]→[30,40]  lst[3:]→[40,50]
lst[::2]→[10,30,50]      lst[:]→[10,20,30,40,50]  shallow copy of sequence
```

Missing slice indication → from start / up to end.
On mutable sequences (`list`), remove with `del lst[3:5]` *and modify with assignment* `lst[1:4]=[15,25]`

Boolean Logic

Comparisons : `< > <= >= == !=` (*boolean results*) ≤ ≥ = ≠

`a and b` logical and — *both simultaneously*

`a or b` logical or — *one or other or both*

pitfall : `and` *and* `or` *return* *value* *of* `a` *or* `b` *(under shortcut evaluation).*
⇒ *ensure that* `a` *and* `b` *are booleans.*

`not a` logical not

`True` `False` — True and False constants

Statements Blocks

```
parent statement:
    statement block 1…
    ⋮
parent statement:
    statement block2…
    ⋮
next statement after block 1
```

indentation !

configure editor to insert 4 spaces in place of an indentation tab.

Modules/Names Imports

module `truc` ⇔ *file* `truc.py`

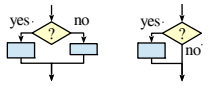
```
from monmod import nom1,nom2 as fct
                →direct access to names, renaming with as
import monmod  →access via monmod.nom1 …
```

modules and packages searched in *python path* (cf `sys.path`)

Conditional Statement

statement block executed only if a condition is true

```
if logical condition:
    statements block
```



Can go with several *elif*, *elif*... and only one final *else*. Only the block of first true condition is executed.

```
if age<=18:
    state="Kid"
elif age>65:
    state="Retired"
else:
    state="Active"
```

with a var `x`:
`if bool(x)==True:` ⇔ `if x:`
`if bool(x)==False:` ⇔ `if not x:`

Maths

floating numbers… approximated values *angles in radians*

Operators: `+ - * / // % **`
Priority `(…)` × ÷ ↑ ↑ a^b
integer ÷ ÷ remainder

`@` → matrix × *python3.5+*`numpy`

```
(1+5.3)*2→12.6
abs(-3.2)→3.2
round(3.57,1)→3.6
pow(4,3)→64.0
```

usual order of operations

```
from math import sin,pi…
sin(pi/4)→0.707…
cos(2*pi/3)→-0.4999…
sqrt(81)→9.0      √
log(e**2)→2.0
ceil(12.5)→13
floor(12.5)→12
```

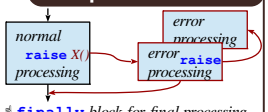
modules `math`, `statistics`, `random`, `decimal`, `fractions`, `numpy`, *etc. (cf. doc)*

Exceptions on Errors

Signaling an error:
`raise` *ExcClass(…)*

Errors processing:

```
try:
    normal procesising block
except Exception as e:
    error processing block
```



`finally` *block for final processing in all cases.*

Conditional Loop Statement

*statements block executed **as long as** condition is true*

```
while logical condition :
    statements block
```


```
s = 0
i = 1
while i <= 100:
    s = s + i**2
    i = i + 1
print("sum:",s)
```

*initializations **before** the loop*
condition with a least one variable value (here `i`)
make condition variable change !

beware of infinite loops!

Loop Control

`break` *immediate exit*
`continue` *next iteration*
`else` *block for **normal** loop exit.*

Algo:

$$s = \sum_{i=1}^{i=100} i^2$$

Display

```
print("v=",3,"cm :",x,",",y+4)
```

items to display : literal values, variables, expressions

`print` options:

- `sep=" "` items separator, default space
- `end="\n"` end of print, default new line
- `file=sys.stdout` print to file, default standard output

Input

```
s = input("Instructions:")
```

`input` always returns a **string**, convert it to required type (cf. boxed *Conversions* on the other side).

Generic Operations on Containers

`len(c)` → items count
`min(c)` `max(c)` `sum(c)`
`sorted(c)` → `list` sorted *copy*
`val in c` → boolean, membership operator `in` (absence `not in`)
`enumerate(c)` → *iterator* on (index, value)
`zip(c1,c2…)` → *iterator* on tuples containing c_i items at same index
`all(c)` → `True` if **all** `c` items evaluated to true, else `False`
`any(c)` → `True` if **at least one** item of `c` evaluated true, else `False`

*Note: For dictionaries and sets, these operations use **keys**.*

*Specific to **ordered sequences containers** (lists, tuples, strings, bytes…)*

`reversed(c)` → *inversed iterator* `c*5` → duplicate `c+c2` → concatenate
`c.index(val)` → *position* `c.count(val)` → *events count*

```
import copy
copy.copy(c) → shallow copy of container
copy.deepcopy(c) → deep copy of container
```

Operations on Lists

modify original list

`lst.append(val)`	add item at end
`lst.extend(seq)`	add sequence of items at end
`lst.insert(idx,val)`	insert item at index
`lst.remove(val)`	remove first item with value *val*
`lst.pop([idx])` →*value*	remove & return item at index *idx* (default last)
`lst.sort()` `lst.reverse()`	sort / reverse liste *in place*

Operations on Dictionaries

`d[key]=value` `d.clear()`
`d[key]` → *value* `del d[key]`
`d.update(d2)` update/add associations
`d.keys()` `d.values()` `d.items()` →*iterable views on keys/values/associations*
`d.pop(key[,default])` → *value*
`d.popitem()` → *(key,value)*
`d.get(key[,default])` → *value*
`d.setdefault(key[,default])` →*value*

Operations on Sets

Operators:
`|` → union (vertical bar char)
`&` → intersection
`-` `^` → difference/symmetric diff.
`<` `<=` `>` `>=` → inclusion relations
Operators also exist as methods.

`s.update(s2)` `s.copy()`
`s.add(key)` `s.remove(key)`
`s.discard(key)` `s.clear()`
`s.pop()`

Files

storing data on disk, and reading it back

```
f = open("file.txt","w",encoding="utf8")
```

- file **variable** for operations
- **name** of file on disk (+path…)
- opening **mode**
  - `'r'` read
  - `'w'` write
  - `'a'` append
  - …`'+'` `'x'` `'b'` `'t'`
- **encoding** of chars for *text files*: `utf8` `ascii` `latin1` …

cf. modules `os`, `os.path` and `pathlib`

writing

```
f.write("coucou")
f.writelines(list of lines)
```

reading

read empty string if end of file

`f.read([n])` → *next chars*
if n not specified, read up to end !
`f.readlines([n])` → *list of next lines*
`f.readline()` → *next line*

*text mode `t` by default (read/write `str`), possible binary mode `b` (read/write `bytes`). **Convert from/to required type** !*

`f.close()` dont forget to **close the file** after use !

`f.flush()` write cache `f.truncate([size])` resize

reading/writing progress sequentially in the file, modifiable with:
`f.tell()` →*position* `f.seek(position[,origin])`

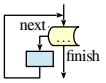
Very common: opening with a guarded block (automatic closing) and reading loop on lines of a text file:

```
with open(…) as f:
    for line in f :
        # processing of line
```

Iterative Loop Statement

*statements block executed **for each** item of a container or iterator*

```
for var in sequence :
    statements block
```



Go over sequence's **values**

```
s = "Some text"
cnt = 0
for c in s:
    if c == "e":
        cnt = cnt + 1
print("found",cnt,"'e'")
```

*initializations **before** the loop*
*loop variable, **assignment managed by `for` statement***
Algo: count number of `e` in the string.

loop on dict/set ⇔ loop on keys sequences
use *slices* to loop on a subset of a sequence

Go over sequence's **index**

- modify item at index
- access items around index (before / after)

```
lst = [11,18,9,12,23,4,17]
lost = []
for idx in range(len(lst)):
    val = lst[idx]
    if val > 15:
        lost.append(val)
        lst[idx] = 15
print("modif:",lst,"-lost:",lost)
```

Algo: limit values greater than 15, memorizing of lost values.

good habit : don't modify loop variable

Go simultaneously over sequence's **index** and **values**:

```
for idx,val in enumerate(lst):
```

Integer Sequences

`range([start,] end [,step])`

start default 0, *end* not included in sequence, *step* signed, default 1

`range(5)` → 0 1 2 3 4 `range(2,12,3)` → 2 5 8 11
`range(3,8)` → 3 4 5 6 7 `range(20,5,-5)` → 20 15 10
`range(len(seq))` → *sequence of index of values in seq*
range provides an immutable sequence of int constructed as needed

Function Definition

function name (identifier)
named parameters

```
def fct(x,y,z):
    """documentation"""
    # statements block, res computation, etc.
    return res
```

`fct`

result value of the call, if no computed result to return: `return None`

parameters and all variables of this block exist only *in* the block and *during* the function call (think of a "black box")

Advanced: `def fct(x,y,z,*args,a=3,b=5,**kwargs):`
**args variable positional arguments (→`tuple`), default values,*
***kwargs variable named arguments (→`dict`)*

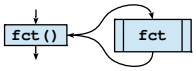
Function Call

```
r = fct(3,i+2,2*i)
```

storage/use of returned value *one argument per parameter*

this is the use of function name *with parentheses* which does the call

*Advanced: *sequence **dict*



Operations on Strings

`s.startswith(prefix[,start[,end]])` `s.endswith(suffix[,start[,end]])` `s.strip([chars])`
`s.count(sub[,start[,end]])` `s.partition(sep)` → *(before,sep,after)*
`s.index(sub[,start[,end]])` `s.find(sub[,start[,end]])`
`s.is…()` *tests on chars categories (ex. `s.isalpha()`)*
`s.upper()` `s.lower()` `s.title()` `s.swapcase()`
`s.casefold()` `s.capitalize()` `s.center([width,fill])`
`s.ljust([width,fill])` `s.rjust([width,fill])` `s.zfill([width])`
`s.encode(encoding)` `s.split([sep])` `s.join(seq)`

Formatting

formating directives — values to format

```
"modele{} {} {}".format(x,y,r) → str
"{selection:formatting!conversion}"
```

- **Selection** :
  `2`
  `nom`
  `0.nom`
  `4[key]`
  `0[2]`
- **Formatting** :
  fill char *alignment* *sign* *mini width*.*precision~maxwidth* *type*
  `< > ^ =` `+ -` *space* `0` at start for filling with 0
  integer: `b` binary, `c` char, `d` decimal (default), `o` octal, `x` or `X` hexa…
  float: `e` or `E` exponential, `f` or `F` fixed point, `g` or `G` appropriate (default),
  string: `s` … `%` percent
- **Conversion** : `s` (readable text) or `r` (literal representation)

Examples:

```
"{:+2.3f}".format(45.72793)
→'+45.728'
"{1:>10s}".format(8,"toto")
→'      toto'
"{x!r}".format(x="I'm")
→'"I\'m"'
```

Data Science Cheat Sheet

Python - Intermediate

KEY BASICS, PRINTING AND GETTING HELP

This cheat sheet assumes you are familiar with the content of our Python Basics Cheat Sheet

`s` - A Python string variable
`i` - A Python integer variable
`f` - A Python float variable
`l` - A Python list variable
`d` - A Python dictionary variable

LISTS

`l.pop(3)` - Returns the fourth item from `l` and deletes it from the list
`l.remove(x)` - Removes the first item in `l` that is equal to `x`
`l.reverse()` - Reverses the order of the items in `l`
`l[1::2]` - Returns every second item from `l`, commencing from the `1`st item
`l[-5:]` - Returns the last 5 items from `l` specific axis

STRINGS

`s.lower()` - Returns a lowercase version of `s`
`s.title()` - Returns `s` with the first letter of every word capitalized
`"23".zfill(4)` - Returns `"0023"` by left-filling the string with `0`'s to make it's length `4`.
`s.splitlines()` - Returns a list by splitting the string on any newline characters.

Python strings share some common methods with lists

`s[:5]` - Returns the first `5` characters of `s`
`"fri" + "end"` - Returns `"friend"`
`"end" in s` - Returns `True` if the substring `"end"` is found in `s`

RANGE

Range objects are useful for creating sequences of integers for looping.

`range(5)` - Returns a sequence from `0` to `4`
`range(2000,2018)` - Returns a sequence from `2000` to `2017`
`range(0,11,2)` - Returns a sequence from `0` to `10`, with each item incrementing by `2`
`range(0,-10,-1)` - Returns a sequence from `0` to `-9`
`list(range(5))` - Returns a list from `0` to `4`

DICTIONARIES

`max(d, key=d.get)` - Return the key that corresponds to the largest value in `d`
`min(d, key=d.get)` - Return the key that corresponds to the smallest value in `d`

SETS

`my_set = set(l)` - Return a `set` object containing the unique values from `l`
`len(my_set)` - Returns the number of objects in `my_set` (or, the number of unique values from `l`)
`a in my_set` - Returns `True` if the value `a` exists in `my_set`

REGULAR EXPRESSIONS

`import re` - Import the Regular Expressions module
`re.search("abc",s)` - Returns a `match` object if the regex `"abc"` is found in `s`, otherwise `None`
`re.sub("abc","xyz",s)` - Returns a string where all instances matching regex `"abc"` are replaced by `"xyz"`

LIST COMPREHENSION

A one-line expression of a for loop

`[i ** 2 for i in range(10)]` - Returns a list of the squares of values from `0` to `9`
`[s.lower() for s in l_strings]` - Returns the list `l_strings`, with each item having had the `.lower()` method applied
`[i for i in l_floats if i < 0.5]` - Returns the items from `l_floats` that are less than `0.5`

FUNCTIONS FOR LOOPING

```
for i, value in enumerate(l):
  print("The value of item {} is {}".
  format(i,value))
```

- Iterate over the list `l`, printing the index location of each item and its value

```
for one, two in zip(l_one,l_two):
  print("one: {}, two: {}".format(one,two))
```

- Iterate over two lists, `l_one` and `l_two` and print each value

```
while x < 10:
  x += 1
```

- Run the code in the body of the loop until the value of `x` is no longer less than `10`

DATETIME

`import datetime as dt` - Import the `datetime` module
`now = dt.datetime.now()` - Assign `datetime` object representing the current time to `now`
`wks4 = dt.datetime.timedelta(weeks=4)` - Assign a `timedelta` object representing a timespan of 4 weeks to `wks4`
`now - wks4` - Return a `datetime` object representing the time 4 weeks prior to `now`
`newyear_2020 = dt.datetime(year=2020, month=12, day=31)` - Assign a `datetime` object representing December 25, 2020 to `newyear_2020`
`newyear_2020.strftime("%A, %b %d, %Y")` - Returns `"Thursday, Dec 31, 2020"`
`dt.datetime.strptime('Dec 31, 2020',"%b %d, %Y")` - Return a `datetime` object representing December 31, 2020

RANDOM

`import random` - Import the `random` module
`random.random()` - Returns a random float between `0.0` and `1.0`
`random.randint(0,10)` - Returns a random integer between `0` and `10`
`random.choice(l)` - Returns a random item from the list `l`

COUNTER

`from collections import Counter` - Import the `Counter` class
`c = Counter(l)` - Assign a `Counter` (dict-like) object with the counts of each unique item from `l`, to `c`
`c.most_common(3)` - Return the 3 most common items from `l`

TRY/EXCEPT

Catch and deal with Errors

`l_ints = [1, 2, 3, "", 5]` - Assign a list of integers with one missing value to `l_ints`

```
l_floats = []
for i in l_ints:
  try:
    l_floats.append(float(i))
  except:
    l_floats.append(i)
```

- Convert each value of `l_ints` to a float, catching and handling `ValueError: could not convert string to float:` where values are missing.

Data Science Cheat Sheet

Python Regular Expressions

SPECIAL CHARACTERS

`^` | Matches the expression to its right at the start of a string. It matches every such instance before each `\n` in the string.

`$` | Matches the expression to its left at the end of a string. It matches every such instance before each `\n` in the string.

`.` | Matches any character except line terminators like `\n`.

`\` | Escapes special characters or denotes character classes.

`A|B` | Matches expression `A` or `B`. If A is matched first, B is left untried.

`+` | Greedily matches the expression to its left 1 or more times.

`*` | Greedily matches the expression to its left 0 or more times.

`?` | Greedily matches the expression to its left 0 or 1 times. But if `?` is added to qualifiers (`+`, `*`, and `?` itself) it will perform matches in a non-greedy manner.

`{m}` | Matches the expression to its left `m` times, and not less.

`{m,n}` | Matches the expression to its left `m` to `n` times, and not less.

`{m,n}?` | Matches the expression to its left `m` times, and ignores `n`. See `?` above.

CHARACTER CLASSES [A.K.A. SPECIAL SEQUENCES]

`\w` | Matches alphanumeric characters, which means `a-z`, `A-Z`, and `0-9`. It also matches the underscore, `_`.

`\d` | Matches digits, which means `0-9`.

`\D` | Matches any non-digits.

`\s` | Matches whitespace characters, which include the `\t`, `\n`, `\r`, and space characters.

`\S` | Matches non-whitespace characters.

`\b` | Matches the boundary (or empty string) at the start and end of a word, that is, between `\w` and `\W`.

`\B` | Matches where `\b` does not, that is, the boundary of `\w` characters.

`\A` | Matches the expression to its right at the absolute start of a string whether in single or multi-line mode.

`\Z` | Matches the expression to its left at the absolute end of a string whether in single or multi-line mode.

SETS

`[ ]` | Contains a set of characters to match.

`[amk]` | Matches either `a`, `m`, or `k`. It does not match `amk`.

`[a-z]` | Matches any alphabet from `a` to `z`.

`[a\-z]` | Matches `a`, `-`, or `z`. It matches `-` because `\` escapes it.

`[a-]` | Matches `a` or `-`, because `-` is not being used to indicate a series of characters.

`[-a]` | As above, matches `a` or `-`.

`[a-z0-9]` | Matches characters from `a` to `z` and also from `0` to `9`.

`[(+*)]` | Special characters become literal inside a set, so this matches `(`, `+`, `*`, and `)`.

`[^ab5]` | Adding `^` excludes any character in the set. Here, it matches characters that are not `a`, `b`, or `5`.

GROUPS

`( )` | Matches the expression inside the parentheses and groups it.

`(?)` | Inside parentheses like this, `?` acts as an extension notation. Its meaning depends on the character immediately to its right.

`(?PAB)` | Matches the expression `AB`, and it can be accessed with the group name.

`(?aiLmsux)` | Here, `a`, `i`, `L`, `m`, `s`, `u`, and `x` are flags:

- `a` — Matches ASCII only
- `i` — Ignore case
- `L` — Locale dependent
- `m` — Multi-line
- `s` — Matches all
- `u` — Matches unicode
- `x` — Verbose

`(?:A)` | Matches the expression as represented by `A`, but unlike `(?PAB)`, it cannot be retrieved afterwards.

`(?#...)` | A comment. Contents are for us to read, not for matching.

`A(?=B)` | Lookahead assertion. This matches the expression `A` only if it is followed by `B`.

`A(?!B)` | Negative lookahead assertion. This matches the expression `A` only if it is not followed by `B`.

`(?<=B)A` | Positive lookbehind assertion. This matches the expression `A` only if `B` is immediately to its left. This can only matched fixed length expressions.

`(?<!B)A` | Negative lookbehind assertion. This matches the expression `A` only if `B` is not immediately to its left. This can only matched fixed length expressions.

`(?P=name)` | Matches the expression matched by an earlier group named “name”.

`(...)\1` | The number `1` corresponds to the first group to be matched. If we want to match more instances of the same expression, simply use its number instead of writing out the whole expression again. We can use from `1` up to `99` such groups and their corresponding numbers.

POPULAR PYTHON RE MODULE FUNCTIONS

`re.findall(A, B)` | Matches all instances of an expression `A` in a string `B` and returns them in a list.

`re.search(A, B)` | Matches the first instance of an expression `A` in a string `B`, and returns it as a re match object.

`re.split(A, B)` | Split a string `B` into a list using the delimiter `A`.

`re.sub(A, B, C)` | Replace `A` with `B` in the string `C`.

Python For Data Science *Cheat Sheet*

Pandas Basics

Learn Python for Data Science Interactively at www.DataCamp.com

Pandas

The **Pandas** library is built on NumPy and provides easy-to-use **data structures** and **data analysis** tools for the Python programming language.

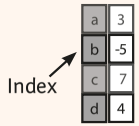
Use the following import convention:

```
>>> import pandas as pd
```

Pandas Data Structures

Series

A **one-dimensional** labeled array capable of holding any data type




```
>>> s = pd.Series([3, -5, 7, 4], index=['a', 'b', 'c', 'd'])
```

DataFrame

Columns

Index	Country	Capital	Population
0	Belgium	Brussels	11190846
1	India	New Delhi	1303171035
2	Brazil	Brasília	207847528

A **two-dimensional** labeled data structure with columns of potentially different types

```
>>> data = {'Country': ['Belgium', 'India', 'Brazil'],
            'Capital': ['Brussels', 'New Delhi', 'Brasília'],
            'Population': [11190846, 1303171035, 207847528]}

>>> df = pd.DataFrame(data,
                      columns=['Country', 'Capital', 'Population'])
```

Asking For Help

```
>>> help(pd.Series.loc)
```

Selection

Also see NumPy Arrays

Getting

```
>>> s['b']
 -5
```
Get one element

```
>>> df[1:]
   Country     Capital  Population
1    India  New Delhi  1303171035
2   Brazil   Brasília   207847528
```
Get subset of a DataFrame

Selecting, Boolean Indexing & Setting

By Position

```
>>> df.iloc[[0],[0]]
'Belgium'
>>> df.iat([0],[0])
'Belgium'
```
Select single value by row & column

By Label

```
>>> df.loc[[0], ['Country']]
'Belgium'
>>> df.at([0], ['Country'])
'Belgium'
```
Select single value by row & column labels

By Label/Position

```
>>> df.ix[2]
Country      Brazil
Capital    Brasília
Population  207847528
```
Select single row of subset of rows

```
>>> df.ix[:,'Capital']
0     Brussels
1    New Delhi
2     Brasília
```
Select a single column of subset of columns

```
>>> df.ix[1,'Capital']
'New Delhi'
```
Select rows and columns

Boolean Indexing

```
>>> s[~(s > 1)]
>>> s[(s < -1) | (s > 2)]
```
Series `s` where value is not >1 `s` where value is <-1 or >2

```
>>> df[df['Population']>1200000000]
```
Use filter to adjust DataFrame

Setting

```
>>> s['a'] = 6
```
Set index `a` of Series `s` to 6

Dropping

```
>>> s.drop(['a', 'c'])
>>> df.drop('Country', axis=1)
```
Drop values from rows (axis=0)
Drop values from columns(axis=1)

Sort & Rank

```
>>> df.sort_index()
>>> df.sort_values(by='Country')
>>> df.rank()
```
Sort by labels along an axis
Sort by the values along an axis
Assign ranks to entries

Retrieving Series/DataFrame Information

Basic Information

```
>>> df.shape
>>> df.index
>>> df.columns
>>> df.info()
>>> df.count()
```
(rows,columns)
Describe index
Describe DataFrame columns
Info on DataFrame
Number of non-NA values

Summary

```
>>> df.sum()
>>> df.cumsum()
>>> df.min()/df.max()
>>> df.idxmin()/df.idxmax()
>>> df.describe()
>>> df.mean()
>>> df.median()
```
Sum of values
Cummulative sum of values
Minimum/maximum values
Minimum/Maximum index value
Summary statistics
Mean of values
Median of values

Applying Functions

```
>>> f = lambda x: x*2
>>> df.apply(f)
>>> df.applymap(f)
```
Apply function
Apply function element-wise

Data Alignment

Internal Data Alignment

NA values are introduced in the indices that don't overlap:

```
>>> s3 = pd.Series([7, -2, 3], index=['a', 'c', 'd'])
>>> s + s3
  a     10.0
  b      NaN
  c      5.0
  d      7.0
```

Arithmetic Operations with Fill Methods

You can also do the internal data alignment yourself with the help of the fill methods:

```
>>> s.add(s3, fill_value=0)
  a    10.0
  b    -5.0
  c    5.0
  d    7.0
>>> s.sub(s3, fill_value=2)
>>> s.div(s3, fill_value=4)
>>> s.mul(s3, fill_value=3)
```

I/O

Read and Write to CSV

```
>>> pd.read_csv('file.csv', header=None, nrows=5)
>>> df.to_csv('myDataFrame.csv')
```

Read and Write to Excel

```
>>> pd.read_excel('file.xlsx')
>>> df.to_excel('dir/myDataFrame.xlsx', sheet_name='Sheet1')
```

Read multiple sheets from the same file

```
>>> xlsx = pd.ExcelFile('file.xls')
>>> df = pd.read_excel(xlsx, 'Sheet1')
```

Read and Write to SQL Query or Database Table

```
>>> from sqlalchemy import create_engine
>>> engine = create_engine('sqlite:///:memory:')
>>> pd.read_sql("SELECT * FROM my_table;", engine)
>>> pd.read_sql_table('my_table', engine)
>>> pd.read_sql_query("SELECT * FROM my_table;", engine)
```

`read_sql()` is a convenience wrapper around `read_sql_table()` and `read_sql_query()`

```
>>> df.to_sql('myDf', engine)
```

Python For Data Science *Cheat Sheet*

Pandas

Learn Python for Data Science **Interactively** at www.DataCamp.com

Reshaping Data

Pivot

```
>>> df3= df2.pivot(index='Date',
                   columns='Type',
                   values='Value')
```

Spread rows into columns

	Date	Type	Value
0	2016-03-01	a	11.432
1	2016-03-02	b	13.031
2	2016-03-01	c	20.784
3	2016-03-03	a	99.906
4	2016-03-02	a	1.303
5	2016-03-03	c	20.784

Type	a	b	c
Date			
2016-03-01	11.432	NaN	20.784
2016-03-02	1.303	13.031	NaN
2016-03-03	99.906	NaN	20.784

Pivot Table

```
>>> df4 = pd.pivot_table(df2,
                         values='Value',
                         index='Date',
                         columns='Type'])
```

Spread rows into columns

Stack / Unstack

```
>>> stacked = df5.stack()
>>> stacked.unstack()
```

Pivot a level of column labels
Pivot a level of index labels

		0	1
1	5	0.233482	0.390959
2	4	0.184713	0.237102
3	3	0.433522	0.429401

Unstacked

1	5	0	0.233482
		1	0.390959
2	4	0	0.184713
		1	0.237102
3	3	0	0.433522
		1	0.429401

Stacked

Melt

```
>>> pd.melt(df2,
            id_vars=["Date"],
            value_vars=["Type", "Value"],
            value_name="Observations")
```

Gather columns into rows

	Date	Type	Value
0	2016-03-01	a	11.432
1	2016-03-02	b	13.031
2	2016-03-01	c	20.784
3	2016-03-03	a	99.906
4	2016-03-02	a	1.303
5	2016-03-03	c	20.784

	Date	Variable	Observations
0	2016-03-01	Type	a
1	2016-03-02	Type	b
2	2016-03-01	Type	c
3	2016-03-03	Type	a
4	2016-03-02	Type	a
5	2016-03-03	Type	c
6	2016-03-01	Value	11.432
7	2016-03-02	Value	13.031
8	2016-03-01	Value	20.784
9	2016-03-03	Value	99.906
10	2016-03-02	Value	1.303
11	2016-03-03	Value	20.784

Iteration

```
>>> df.iteritems()
>>> df.iterrows()
```

(Column-index, Series) pairs
(Row-index, Series) pairs

Advanced Indexing

Also see NumPy Arrays

Selecting

```
>>> df3.loc[:,(df3>1).any()]
>>> df3.loc[:,(df3>1).all()]
>>> df3.loc[:,df3.isnull().any()]
>>> df3.loc[:,df3.notnull().all()]
```

Select cols with any vals >1
Select cols with vals > 1
Select cols with NaN
Select cols without NaN

Indexing With isin

```
>>> df[(df.Country.isin(df2.Type))]
>>> df3.filter(items="a","b"])
>>> df.select(lambda x: not x%5)
```

Find same elements
Filter on values
Select specific elements

Where

```
>>> s.where(s > 0)
```

Subset the data

Query

```
>>> df6.query('second > first')
```

Query DataFrame

Setting/Resetting Index

```
>>> df.set_index('Country')
>>> df4 = df.reset_index()
>>> df = df.rename(index=str,
                   columns={"Country":"cntry",
                            "Capital":"cptl",
                            "Population":"ppltn"})
```

Set the index
Reset the index
Rename DataFrame

Reindexing

```
>>> s2 = s.reindex(['a','c','d','e','b'])
```

Forward Filling

```
>>> df.reindex(range(4),
               method='ffill')
```

	Country	Capital	Population
0	Belgium	Brussels	11190846
1	India	New Delhi	1303171035
2	Brazil	Brasília	207847528
3	Brazil	Brasília	207847528

Backward Filling

```
>>> s3 = s.reindex(range(5),
                   method='bfill')
```

0	3
1	3
2	3
3	3
4	3

MultiIndexing

```
>>> arrays = [np.array([1,2,3]),
              np.array([5,4,3])]
>>> df5 = pd.DataFrame(np.random.rand(3, 2), index=arrays)
>>> tuples = list(zip(*arrays))
>>> index = pd.MultiIndex.from_tuples(tuples,
                                      names=['first', 'second'])
>>> df6 = pd.DataFrame(np.random.rand(3, 2), index=index)
>>> df2.set_index(["Date", "Type"])
```

Duplicate Data

```
>>> s3.unique()
>>> df2.duplicated('Type')
>>> df2.drop_duplicates('Type', keep='last')
>>> df.index.duplicated()
```

Return unique values
Check duplicates
Drop duplicates
Check index duplicates

Grouping Data

Aggregation

```
>>> df2.groupby(by=['Date','Type']).mean()
>>> df4.groupby(level=0).sum()
>>> df4.groupby(level=0).agg({'a':lambda x:sum(x)/len(x),
                              'b': np.sum})
```

Transformation

```
>>> customSum = lambda x: (x+x%2)
>>> df4.groupby(level=0).transform(customSum)
```

Missing Data

```
>>> df.dropna()
>>> df3.fillna(df3.mean())
>>> df2.replace("a", "f")
```

Drop NaN values
Fill NaN values with a predetermined value
Replace values with others

Combining Data

data1

	X1	X2
a	11.432
b	1.303
c	99.906

data2

	X1	X3
a	20.784
b	NaN
d	20.784

Merge

```
>>> pd.merge(data1,
             data2,
             how='left',
             on='X1')
```

	X1	X2	X3
a	11.432	20.784
b	1.303	NaN
c	99.906	NaN

```
>>> pd.merge(data1,
             data2,
             how='right',
             on='X1')
```

	X1	X2	X3
a	11.432	20.784
b	1.303	NaN
d	NaN	20.784

```
>>> pd.merge(data1,
             data2,
             how='inner',
             on='X1')
```

	X1	X2	X3
a	11.432	20.784
b	1.303	NaN

```
>>> pd.merge(data1,
             data2,
             how='outer',
             on='X1')
```

	X1	X2	X3
a	11.432	20.784
b	1.303	NaN
c	99.906	NaN
d	NaN	20.784

Join

```
>>> data1.join(data2, how='right')
```

Concatenate

Vertical

```
>>> s.append(s2)
```

Horizontal/Vertical

```
>>> pd.concat([s,s2],axis=1, keys=['One','Two'])
>>> pd.concat([data1, data2], axis=1, join='inner')
```

Dates

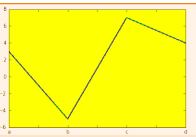
```
>>> df2['Date']= pd.to_datetime(df2['Date'])
>>> df2['Date']= pd.date_range('2000-1-1',
                               periods=6,
                               freq='M')
>>> dates = [datetime(2012,5,1), datetime(2012,5,2)]
>>> index = pd.DatetimeIndex(dates)
>>> index = pd.date_range(datetime(2012,2,1), end, freq='BM')
```

Visualization

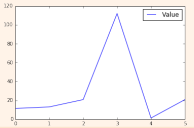
Also see Matplotlib

```
>>> import matplotlib.pyplot as plt
```

```
>>> s.plot()
>>> plt.show()
```



```
>>> df2.plot()
>>> plt.show()
```

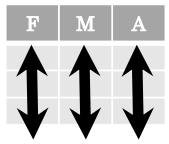


Data Wrangling with pandas Cheat Sheet

http://pandas.pydata.org

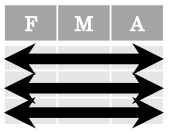
Tidy Data – A foundation for wrangling in pandas

In a tidy data set:



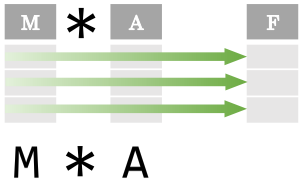
Each **variable** is saved in its own **column**

&



Each **observation** is saved in its own **row**

Tidy data complements pandas's **vectorized operations**. pandas will automatically preserve observations as you manipulate variables. No other format works as intuitively with pandas.



Syntax – Creating DataFrames

	a	b	c
1	4	7	10
2	5	8	11
3	6	9	12

```
df = pd.DataFrame(
          {"a" : [4 ,5, 6],
           "b" : [7, 8, 9],
           "c" : [10, 11, 12]},
         index = [1, 2, 3])
```

Specify values for each column.

```
df = pd.DataFrame(
     [[4, 7, 10],
      [5, 8, 11],
      [6, 9, 12]],
     index=[1, 2, 3],
     columns=['a', 'b', 'c'])
```

Specify values for each row.

		a	b	c
n	v			
d	1	4	7	10
	2	5	8	11
e	2	6	9	12

```
df = pd.DataFrame(
          {"a" : [4 ,5, 6],
           "b" : [7, 8, 9],
           "c" : [10, 11, 12]},
index = pd.MultiIndex.from_tuples(
          [('d',1),('d',2),('e',2)],
            names=['n','v']))
```

Create DataFrame with a MultiIndex

Method Chaining

Most pandas methods return a DataFrame so that another pandas method can be applied to the result. This improves readability of code.

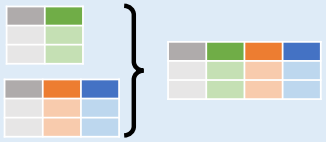
```
df = (pd.melt(df)
        .rename(columns={
                'variable' : 'var',
                'value' : 'val'})
        .query('val >= 200')
     )
```

Reshaping Data – Change the layout of a data set

pd.melt(df)
Gather columns into rows.

df.pivot(columns='var', values='val')
Spread rows into columns.

pd.concat([df1,df2])
Append rows of DataFrames



pd.concat([df1,df2], axis=1)
Append columns of DataFrames

df.sort_values('mpg')
Order rows by values of a column (low to high).

df.sort_values('mpg',ascending=False)
Order rows by values of a column (high to low).

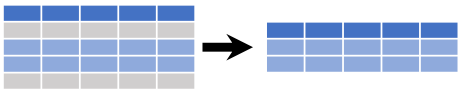
df.rename(columns = {'y':'year'})
Rename the columns of a DataFrame

df.sort_index()
Sort the index of a DataFrame

df.reset_index()
Reset index of DataFrame to row numbers, moving index to columns.

df.drop(columns=['Length','Height'])
Drop columns from DataFrame

Subset Observations (Rows)



df[df.Length > 7]
Extract rows that meet logical criteria.

df.drop_duplicates()
Remove duplicate rows (only considers columns).

df.head(n)
Select first n rows.

df.tail(n)
Select last n rows.

df.sample(frac=0.5)
Randomly select fraction of rows.

df.sample(n=10)
Randomly select n rows.

df.iloc[10:20]
Select rows by position.

df.nlargest(n, 'value')
Select and order top n entries.

df.nsmallest(n, 'value')
Select and order bottom n entries.

Logic in Python (and pandas)			
<	Less than	!=	Not equal to
>	Greater than	df.column.isin(*values*)	Group membership
==	Equals	pd.isnull(*obj*)	Is NaN
<=	Less than or equals	pd.notnull(*obj*)	Is not NaN
>=	Greater than or equals	&,|,~,^,df.any(),df.all()	Logical and, or, not, xor, any, all

Subset Variables (Columns)

df[['width','length','species']]
Select multiple columns with specific names.

df['width'] *or* **df.width**
Select single column with specific name.

df.filter(regex='*regex*')
Select columns whose name matches regular expression *regex*.

regex (Regular Expressions) Examples	
'\.'	Matches strings containing a period '.'
'Length$'	Matches strings ending with word 'Length'
'^Sepal'	Matches strings beginning with the word 'Sepal'
'^x[1-5]$'	Matches strings beginning with 'x' and ending with 1,2,3,4,5
'^(?!Species$).*'	Matches strings except the string 'Species'

df.loc[:,'x2':'x4']
Select all columns between x2 and x4 (inclusive).

df.iloc[:,[1,2,5]]
Select columns in positions 1, 2 and 5 (first column is 0).

df.loc[df['a'] > 10, ['a','c']]
Select rows meeting logical condition, and only the specific columns .

http://pandas.pydata.org/ This cheat sheet inspired by Rstudio Data Wrangling Cheatsheet (https://www.rstudio.com/wp-content/uploads/2015/02/data-wrangling-cheatsheet.pdf) Written by Irv Lustig, Princeton Consultants

Summarize Data

`df['w'].value_counts()`
Count number of rows with each unique value of variable

`len(df)`
# of rows in DataFrame.

`df['w'].nunique()`
# of distinct values in a column.

`df.describe()`
Basic descriptive statistics for each column (or GroupBy)

pandas provides a large set of **summary functions** that operate on different kinds of pandas objects (DataFrame columns, Series, GroupBy, Expanding and Rolling (see below)) and produce single values for each of the groups. When applied to a DataFrame, the result is returned as a pandas Series for each column. Examples:

`sum()`
Sum values of each object.

`count()`
Count non-NA/null values of each object.

`median()`
Median value of each object.

`quantile([0.25,0.75])`
Quantiles of each object.

`apply(function)`
Apply function to each object.

`min()`
Minimum value in each object.

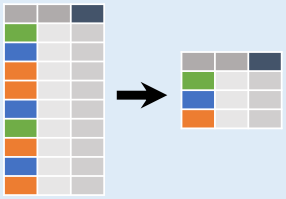
`max()`
Maximum value in each object.

`mean()`
Mean value of each object.

`var()`
Variance of each object.

`std()`
Standard deviation of each object.

Group Data



`df.groupby(by="col")`
Return a GroupBy object, grouped by values in column named "col".

`df.groupby(level="ind")`
Return a GroupBy object, grouped by values in index level named "ind".

All of the summary functions listed above can be applied to a group.
Additional GroupBy functions:

`size()`
Size of each group.

`agg(function)`
Aggregate group using function.

The examples below can also be applied to groups. In this case, the function is applied on a per-group basis, and the returned vectors are of the length of the original DataFrame.

`shift(1)`
Copy with values shifted by 1.

`rank(method='dense')`
Ranks with no gaps.

`rank(method='min')`
Ranks. Ties get min rank.

`rank(pct=True)`
Ranks rescaled to interval [0, 1].

`rank(method='first')`
Ranks. Ties go to first value.

`shift(-1)`
Copy with values lagged by 1.

`cumsum()`
Cumulative sum.

`cummax()`
Cumulative max.

`cummin()`
Cumulative min.

`cumprod()`
Cumulative product.

Windows

`df.expanding()`
Return an Expanding object allowing summary functions to be applied cumulatively.

`df.rolling(n)`
Return a Rolling object allowing summary functions to be applied to windows of length n.

Handling Missing Data

`df.dropna()`
Drop rows with any column having NA/null data.

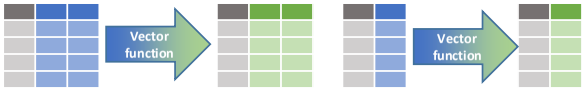
`df.fillna(value)`
Replace all NA/null data with value.

Make New Columns

`df.assign(Area=lambda df: df.Length*df.Height)`
Compute and append one or more new columns.

`df['Volume'] = df.Length*df.Height*df.Depth`
Add single column.

`pd.qcut(df.col, n, labels=False)`
Bin column into n buckets.



pandas provides a large set of **vector functions** that operate on all columns of a DataFrame or a single selected column (a pandas Series). These functions produce vectors of values for each of the columns, or a single Series for the individual Series. Examples:

`max(axis=1)`
Element-wise max.

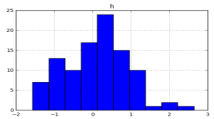
`min(axis=1)`
Element-wise min.

`clip(lower=-10,upper=10)`
Trim values at input thresholds

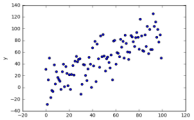
`abs()`
Absolute value.

Plotting

`df.plot.hist()`
Histogram for each column



`df.plot.scatter(x='w',y='h')`
Scatter chart using pairs of points



Combine Data Sets

adf

x1	x2
A	1
B	2
C	3

+

bdf

x1	x3
A	T
B	F
D	T

=

Standard Joins

x1	x2	x3
A	1	T
B	2	F
C	3	NaN

`pd.merge(adf, bdf, how='left', on='x1')`
Join matching rows from bdf to adf.

x1	x2	x3
A	1.0	T
B	2.0	F
D	NaN	T

`pd.merge(adf, bdf, how='right', on='x1')`
Join matching rows from adf to bdf.

x1	x2	x3
A	1	T
B	2	F

`pd.merge(adf, bdf, how='inner', on='x1')`
Join data. Retain only rows in both sets.

x1	x2	x3
A	1	T
B	2	F
C	3	NaN
D	NaN	T

`pd.merge(adf, bdf, how='outer', on='x1')`
Join data. Retain all values, all rows.

Filtering Joins

x1	x2
A	1
B	2

`adf[adf.x1.isin(bdf.x1)]`
All rows in adf that have a match in bdf.

x1	x2
C	3

`adf[~adf.x1.isin(bdf.x1)]`
All rows in adf that do not have a match in bdf.

ydf

x1	x2
A	1
B	2
C	3

+

zdf

x1	x2
B	2
C	3
D	4

=

Set-like Operations

x1	x2
B	2
C	3

`pd.merge(ydf, zdf)`
Rows that appear in both ydf and zdf (Intersection).

x1	x2
A	1
B	2
C	3
D	4

`pd.merge(ydf, zdf, how='outer')`
Rows that appear in either or both ydf and zdf (Union).

x1	x2
A	1

```
pd.merge(ydf, zdf, how='outer',
         indicator=True)
.query('_merge == "left_only"')
.drop(columns=['_merge'])
```
Rows that appear in ydf but not zdf (Setdiff).

Python For Data Science *Cheat Sheet*

NumPy Basics

Learn Python for Data Science Interactively at www.DataCamp.com

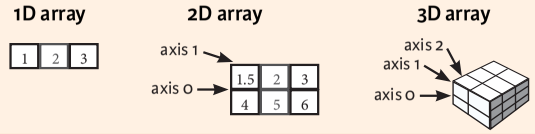
NumPy

The **NumPy** library is the core library for scientific computing in Python. It provides a high-performance multidimensional array object, and tools for working with these arrays.

Use the following import convention:

```
>>> import numpy as np
```

NumPy Arrays



Creating Arrays

```
>>> a = np.array([1,2,3])
>>> b = np.array([(1.5,2,3), (4,5,6)], dtype = float)
>>> c = np.array([[(1.5,2,3), (4,5,6)], [(3,2,1), (4,5,6)]],
                 dtype = float)
```

Initial Placeholders

```
>>> np.zeros((3,4))                  Create an array of zeros
>>> np.ones((2,3,4),dtype=np.int16)  Create an array of ones
>>> d = np.arange(10,25,5)           Create an array of evenly
                                     spaced values (step value)
>>> np.linspace(0,2,9)               Create an array of evenly
                                     spaced values (number of samples)
>>> e = np.full((2,2),7)             Create a constant array
>>> f = np.eye(2)                    Create a 2X2 identity matrix
>>> np.random.random((2,2))          Create an array with random values
>>> np.empty((3,2))                  Create an empty array
```

I/O

Saving & Loading On Disk

```
>>> np.save('my_array', a)
>>> np.savez('array.npz', a, b)
>>> np.load('my_array.npy')
```

Saving & Loading Text Files

```
>>> np.loadtxt("myfile.txt")
>>> np.genfromtxt("my_file.csv", delimiter=',')
>>> np.savetxt("myarray.txt", a, delimiter=" ")
```

Data Types

```
>>> np.int64       Signed 64-bit integer types
>>> np.float32     Standard double-precision floating point
>>> np.complex     Complex numbers represented by 128 floats
>>> np.bool        Boolean type storing TRUE and FALSE values
>>> np.object      Python object type
>>> np.string_     Fixed-length string type
>>> np.unicode_    Fixed-length unicode type
```

Inspecting Your Array

```
>>> a.shape          Array dimensions
>>> len(a)           Length of array
>>> b.ndim           Number of array dimensions
>>> e.size           Number of array elements
>>> b.dtype          Data type of array elements
>>> b.dtype.name     Name of data type
>>> b.astype(int)    Convert an array to a different type
```

Asking For Help

```
>>> np.info(np.ndarray.dtype)
```

Array Mathematics

Arithmetic Operations

```
>>> g = a - b                        Subtraction
  array([[-0.5,  0. ,  0. ],
         [-3. , -3. , -3. ]])
>>> np.subtract(a,b)                 Subtraction
>>> b + a                            Addition
  array([[ 2.5,  4. ,  6. ],
         [ 5. ,  7. ,  9. ]])
>>> np.add(b,a)                      Addition
>>> a / b                            Division
  array([[ 0.66666667,  1.        ,  1.        ],
         [ 0.25      ,  0.4       ,  0.5       ]])
>>> np.divide(a,b)                   Division
>>> a * b                            Multiplication
  array([[  1.5,   4. ,   9. ],
         [  4. ,  10. ,  18. ]])
>>> np.multiply(a,b)                 Multiplication
>>> np.exp(b)                        Exponentiation
>>> np.sqrt(b)                       Square root
>>> np.sin(a)                        Print sines of an array
>>> np.cos(b)                        Element-wise cosine
>>> np.log(a)                        Element-wise natural logarithm
>>> e.dot(f)                         Dot product
  array([[ 7.,  7.],
         [ 7.,  7.]])
```

Comparison

```
>>> a == b                           Element-wise comparison
  array([[False,  True,  True],
         [False, False, False]], dtype=bool)
>>> a < 2                            Element-wise comparison
  array([True, False, False], dtype=bool)
>>> np.array_equal(a, b)             Array-wise comparison
```

Aggregate Functions

```
>>> a.sum()                          Array-wise sum
>>> a.min()                          Array-wise minimum value
>>> b.max(axis=0)                    Maximum value of an array row
>>> b.cumsum(axis=1)                 Cumulative sum of the elements
>>> a.mean()                         Mean
>>> b.median()                       Median
>>> a.corrcoef()                     Correlation coefficient
>>> np.std(b)                        Standard deviation
```

Copying Arrays

```
>>> h = a.view()          Create a view of the array with the same data
>>> np.copy(a)            Create a copy of the array
>>> h = a.copy()          Create a deep copy of the array
```

Sorting Arrays

```
>>> a.sort()              Sort an array
>>> c.sort(axis=0)        Sort the elements of an array's axis
```

Subsetting, Slicing, Indexing

Also see Lists

Subsetting

```
>>> a[2]                             Select the element at the 2nd index
  3
>>> b[1,2]                           Select the element at row 1 column 2
  6.0                                (equivalent to b[1][2])
```

Slicing

```
>>> a[0:2]                           Select items at index 0 and 1
  array([1, 2])
>>> b[0:2,1]                         Select items at rows 0 and 1 in column 1
  array([ 2.,  5.])
>>> b[:1]                            Select all items at row 0
  array([[1.5, 2., 3.]])             (equivalent to b[0:1, :])
>>> c[1,...]                         Same as [1,:,:]
  array([[[ 3.,  2.,  1.],
          [ 4.,  5.,  6.]]])
>>> a[ : :-1]                        Reversed array a
  array([3, 2, 1])
```

Boolean Indexing

```
>>> a[a<2]                           Select elements from a less than 2
  array([1])
```

Fancy Indexing

```
>>> b[[1, 0, 1, 0],[0, 1, 2, 0]]    Select elements (1,0),(0,1),(1,2) and (0,0)
  array([ 4. , 2. , 6. , 1.5])
>>> b[[1, 0, 1, 0]][:,[0,1,2,0]]    Select a subset of the matrix's rows
  array([[ 4. ,5. , 6. , 4. ],       and columns
         [ 1.5, 2. , 3. , 1.5],
         [ 4. , 5. , 6. , 4. ],
         [ 1.5, 2. , 3. , 1.5]])
```

Array Manipulation

Transposing Array

```
>>> i = np.transpose(b)              Permute array dimensions
>>> i.T                              Permute array dimensions
```

Changing Array Shape

```
>>> b.ravel()                        Flatten the array
>>> g.reshape(3,-2)                  Reshape, but don't change data
```

Adding/Removing Elements

```
>>> h.resize((2,6))                  Return a new array with shape (2,6)
>>> np.append(h,g)                   Append items to an array
>>> np.insert(a, 1, 5)               Insert items in an array
>>> np.delete(a,[1])                 Delete items from an array
```

Combining Arrays

```
>>> np.concatenate((a,d),axis=0)     Concatenate arrays
  array([ 1,  2,  3, 10, 15, 20])
>>> np.vstack((a,b))                 Stack arrays vertically (row-wise)
  array([[ 1. ,  2. ,  3. ],
         [ 1.5,  2. ,  3. ],
         [ 4. ,  5. ,  6. ]])
>>> np.r_[e,f]                       Stack arrays vertically (row-wise)
>>> np.hstack((e,f))                 Stack arrays horizontally (column-wise)
  array([[ 7.,  7.,  1.,  0.],
         [ 7.,  7.,  0.,  1.]])
>>> np.column_stack((a,d))           Create stacked column-wise arrays
  array([[ 1, 10],
         [ 2, 15],
         [ 3, 20]])
>>> np.c_[a,d]                       Create stacked column-wise arrays
```

Splitting Arrays

```
>>> np.hsplit(a,3)                   Split the array horizontally at the 3rd
  [array([1]),array([2]),array([3])]  index
>>> np.vsplit(c,2)                   Split the array vertically at the 2nd index
[array([[[ 1.5,  2. ,  1. ],
         [ 4. ,  5. ,  6. ]]]),
 array([[[ 3.,  2.,  3.],
         [ 4.,  5.,  6.]]])]
```

Python For Data Science *Cheat Sheet*

Importing Data

Learn Python for data science Interactively at www.DataCamp.com

Importing Data in Python

Most of the time, you'll use either **NumPy** or **pandas** to import your data:

```
>>> import numpy as np
>>> import pandas as pd
```

Help

```
>>> np.info(np.ndarray.dtype)
>>> help(pd.read_csv)
```

Text Files

Plain Text Files

```
>>> filename = 'huck_finn.txt'
>>> file = open(filename, mode='r')  # Open the file for reading
>>> text = file.read()               # Read a file's contents
>>> print(file.closed)               # Check whether file is closed
>>> file.close()                     # Close file
>>> print(text)
```

Using the context manager `with`

```
>>> with open('huck_finn.txt', 'r') as file:
        print(file.readline())        # Read a single line
        print(file.readline())
        print(file.readline())
```

Table Data: Flat Files

Importing Flat Files with numpy

Files with one data type

```
>>> filename = 'mnist.txt'
>>> data = np.loadtxt(filename,
                      delimiter=',',  # String used to separate values
                      skiprows=2,     # Skip the first 2 lines
                      usecols=[0,2],  # Read the 1st and 3rd column
                      dtype=str)      # The type of the resulting array
```

Files with mixed data types

```
>>> filename = 'titanic.csv'
>>> data = np.genfromtxt(filename,
                         delimiter=',',
                         names=True,  # Look for column header
                         dtype=None)
```

```
>>> data_array = np.recfromcsv(filename)
```

The default `dtype` of the `np.recfromcsv()` function is `None`.

Importing Flat Files with pandas

```
>>> filename = 'winequality-red.csv'
>>> data = pd.read_csv(filename,
                       nrows=5,          # Number of rows of file to read
                       header=None,      # Row number to use as col names
                       sep='\t',         # Delimiter to use
                       comment='#',      # Character to split comments
                       na_values=[""])   # String to recognize as NA/NaN
```

Excel Spreadsheets

```
>>> file = 'urbanpop.xlsx'
>>> data = pd.ExcelFile(file)
>>> df_sheet2 = data.parse('1960-1966',
                           skiprows=[0],
                           names=['Country',
                                  'AAM: War(2002)'])
>>> df_sheet1 = data.parse(0,
                           parse_cols=[0],
                           skiprows=[0],
                           names=['Country'])
```

To access the sheet names, use the `sheet_names` attribute:

```
>>> data.sheet_names
```

SAS Files

```
>>> from sas7bdat import SAS7BDAT
>>> with SAS7BDAT('urbanpop.sas7bdat') as file:
        df_sas = file.to_data_frame()
```

Stata Files

```
>>> data = pd.read_stata('urbanpop.dta')
```

Relational Databases

```
>>> from sqlalchemy import create_engine
>>> engine = create_engine('sqlite://Northwind.sqlite')
```

Use the `table_names()` method to fetch a list of table names:

```
>>> table_names = engine.table_names()
```

Querying Relational Databases

```
>>> con = engine.connect()
>>> rs = con.execute("SELECT * FROM Orders")
>>> df = pd.DataFrame(rs.fetchall())
>>> df.columns = rs.keys()
>>> con.close()
```

Using the context manager `with`

```
>>> with engine.connect() as con:
        rs = con.execute("SELECT OrderID FROM Orders")
        df = pd.DataFrame(rs.fetchmany(size=5))
        df.columns = rs.keys()
```

Querying relational databases with pandas

```
>>> df = pd.read_sql_query("SELECT * FROM Orders", engine)
```

Exploring Your Data

NumPy Arrays

```
>>> data_array.dtype      # Data type of array elements
>>> data_array.shape      # Array dimensions
>>> len(data_array)       # Length of array
```

pandas DataFrames

```
>>> df.head()             # Return first DataFrame rows
>>> df.tail()             # Return last DataFrame rows
>>> df.index              # Describe index
>>> df.columns            # Describe DataFrame columns
>>> df.info()             # Info on DataFrame
>>> data_array = data.values  # Convert a DataFrame to an a NumPy array
```

Pickled Files

```
>>> import pickle
>>> with open('pickled_fruit.pkl', 'rb') as file:
        pickled_data = pickle.load(file)
```

HDF5 Files

```
>>> import h5py
>>> filename = 'H-H1_LOSC_4_v1-815411200-4096.hdf5'
>>> data = h5py.File(filename, 'r')
```

Matlab Files

```
>>> import scipy.io
>>> filename = 'workspace.mat'
>>> mat = scipy.io.loadmat(filename)
```

Exploring Dictionaries

Accessing Elements with Functions

```
>>> print(mat.keys())             # Print dictionary keys
>>> for key in data.keys():       # Print dictionary keys
        print(key)
meta
quality
strain
>>> pickled_data.values()         # Return dictionary values
>>> print(mat.items())            # Returns items in list format of (key, value) tuple pairs
```

Accessing Data Items with Keys

```
>>> for key in data ['meta'].keys()   # Explore the HDF5 structure
        print(key)
Description
DescriptionURL
Detector
Duration
GPSstart
Observatory
Type
UTCstart
>>> print(data['meta']['Description'].value)  # Retrieve the value for a key
```

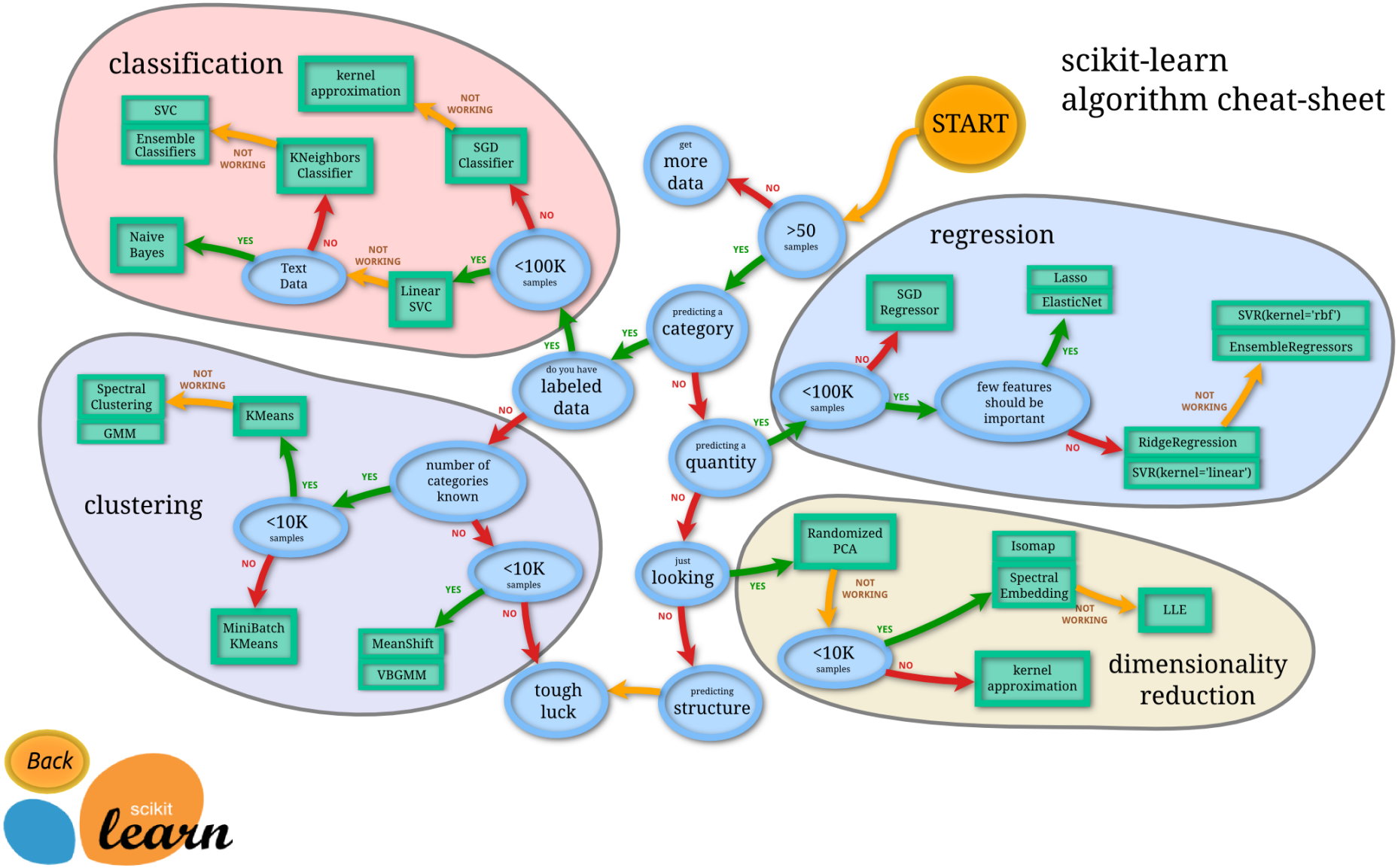
Navigating Your FileSystem

Magic Commands

```
!ls          # List directory contents of files and directories
%cd ..       # Change current working directory
%pwd         # Return the current working directory path
```

`os` Library

```
>>> import os
>>> path = "/usr/tmp"
>>> wd = os.getcwd()                  # Store the name of current directory in a string
>>> os.listdir(wd)                    # Output contents of the directory in a list
>>> os.chdir(path)                    # Change current working directory
>>> os.rename("test1.txt",            # Rename a file
              "test2.txt")
>>> os.remove("test1.txt")            # Delete an existing file
>>> os.mkdir("newdir")                # Create a new directory
```



scikit-learn
algorithm cheat-sheet
START
>50 samples
NO
get more data
YES
predicting a category
YES
NO
do you have labeled data
YES
NO
predicting a quantity
YES
NO
just looking
YES
NO
predicting structure
tough luck
classification
kernel approximation
NOT WORKING
SVC
Ensemble Classifiers
NOT WORKING
KNeighbors Classifier
SGD Classifier
NO
Naive Bayes
YES
Text Data
NO
NOT WORKING
Linear SVC
YES
<100K samples
YES
regression
SGD Regressor
Lasso
ElasticNet
NO
<100K samples
YES
few features should be important
YES
NO
SVR(kernel='rbf')
EnsembleRegressors
NOT WORKING
RidgeRegression
SVR(kernel='linear')
clustering
Spectral Clustering
GMM
NOT WORKING
KMeans
YES
number of categories known
YES
NO
<10K samples
NO
MiniBatch KMeans
<10K samples
YES
NO
MeanShift
VBGMM
dimensionality reduction
Randomized PCA
YES
NOT WORKING
Isomap
Spectral Embedding
NOT WORKING
LLE
YES
<10K samples
NO
kernel approximation
Back
scikit learn

Python For Data Science *Cheat Sheet*

Scikit-Learn

Learn Python for data science Interactively at www.DataCamp.com

Scikit-learn

Scikit-learn is an open source Python library that implements a range of machine learning, preprocessing, cross-validation and visualization algorithms using a unified interface.

A Basic Example

```
>>> from sklearn import neighbors, datasets, preprocessing
>>> from sklearn.model_selection import train_test_split
>>> from sklearn.metrics import accuracy_score
>>> iris = datasets.load_iris()
>>> X, y = iris.data[:, :2], iris.target
>>> X_train, X_test, y_train, y_test= train_test_split(X, y, random_state=33)
>>> scaler = preprocessing.StandardScaler().fit(X_train)
>>> X_train = scaler.transform(X_train)
>>> X_test = scaler.transform(X_test)
>>> knn = neighbors.KNeighborsClassifier(n_neighbors=5)
>>> knn.fit(X_train, y_train)
>>> y_pred = knn.predict(X_test)
>>> accuracy_score(y_test, y_pred)
```

Loading The Data

Also see NumPy & Pandas

Your data needs to be numeric and stored as NumPy arrays or SciPy sparse matrices. Other types that are convertible to numeric arrays, such as Pandas DataFrame, are also acceptable.

```
>>> import numpy as np
>>> X = np.random.random((10,5))
>>> y = np.array(['M','M','F','F','M','F','M','M','F','F','F'])
>>> X[X < 0.7] = 0
```

Training And Test Data

```
>>> from sklearn.model_selection import train_test_split
>>> X_train, X_test, y_train, y_test = train_test_split(X,
                                                        y,
                                                        random_state=0)
```

Create Your Model

Supervised Learning Estimators

Linear Regression

```
>>> from sklearn.linear_model import LinearRegression
>>> lr = LinearRegression(normalize=True)
```

Support Vector Machines (SVM)

```
>>> from sklearn.svm import SVC
>>> svc = SVC(kernel='linear')
```

Naive Bayes

```
>>> from sklearn.naive_bayes import GaussianNB
>>> gnb = GaussianNB()
```

KNN

```
>>> from sklearn import neighbors
>>> knn = neighbors.KNeighborsClassifier(n_neighbors=5)
```

Unsupervised Learning Estimators

Principal Component Analysis (PCA)

```
>>> from sklearn.decomposition import PCA
>>> pca = PCA(n_components=0.95)
```

K Means

```
>>> from sklearn.cluster import KMeans
>>> k_means = KMeans(n_clusters=3, random_state=0)
```

Model Fitting

Supervised learning	
`>>> lr.fit(X, y)`	Fit the model to the data
`>>> knn.fit(X_train, y_train)`	
`>>> svc.fit(X_train, y_train)`	
Unsupervised Learning	
`>>> k_means.fit(X_train)`	Fit the model to the data
`>>> pca_model = pca.fit_transform(X_train)`	Fit to data, then transform it

Prediction

Supervised Estimators	
`>>> y_pred = svc.predict(np.random.random((2,5)))`	Predict labels
`>>> y_pred = lr.predict(X_test)`	Predict labels
`>>> y_pred = knn.predict_proba(X_test)`	Estimate probability of a label
Unsupervised Estimators	
`>>> y_pred = k_means.predict(X_test)`	Predict labels in clustering algos

Preprocessing The Data

Standardization

```
>>> from sklearn.preprocessing import StandardScaler
>>> scaler = StandardScaler().fit(X_train)
>>> standardized_X = scaler.transform(X_train)
>>> standardized_X_test = scaler.transform(X_test)
```

Normalization

```
>>> from sklearn.preprocessing import Normalizer
>>> scaler = Normalizer().fit(X_train)
>>> normalized_X = scaler.transform(X_train)
>>> normalized_X_test = scaler.transform(X_test)
```

Binarization

```
>>> from sklearn.preprocessing import Binarizer
>>> binarizer = Binarizer(threshold=0.0).fit(X)
>>> binary_X = binarizer.transform(X)
```

Encoding Categorical Features

```
>>> from sklearn.preprocessing import LabelEncoder
>>> enc = LabelEncoder()
>>> y = enc.fit_transform(y)
```

Imputing Missing Values

```
>>> from sklearn.preprocessing import Imputer
>>> imp = Imputer(missing_values=0, strategy='mean', axis=0)
>>> imp.fit_transform(X_train)
```

Generating Polynomial Features

```
>>> from sklearn.preprocessing import PolynomialFeatures
>>> poly = PolynomialFeatures(5)
>>> poly.fit_transform(X)
```

Evaluate Your Model's Performance

Classification Metrics

Accuracy Score

```
>>> knn.score(X_test, y_test)
```
Estimator score method

```
>>> from sklearn.metrics import accuracy_score
>>> accuracy_score(y_test, y_pred)
```
Metric scoring functions

Classification Report

```
>>> from sklearn.metrics import classification_report
>>> print(classification_report(y_test, y_pred))
```
Precision, recall, f1-score and support

Confusion Matrix

```
>>> from sklearn.metrics import confusion_matrix
>>> print(confusion_matrix(y_test, y_pred))
```

Regression Metrics

Mean Absolute Error

```
>>> from sklearn.metrics import mean_absolute_error
>>> y_true = [3, -0.5, 2]
>>> mean_absolute_error(y_true, y_pred)
```

Mean Squared Error

```
>>> from sklearn.metrics import mean_squared_error
>>> mean_squared_error(y_test, y_pred)
```

R^2 Score

```
>>> from sklearn.metrics import r2_score
>>> r2_score(y_true, y_pred)
```

Clustering Metrics

Adjusted Rand Index

```
>>> from sklearn.metrics import adjusted_rand_score
>>> adjusted_rand_score(y_true, y_pred)
```

Homogeneity

```
>>> from sklearn.metrics import homogeneity_score
>>> homogeneity_score(y_true, y_pred)
```

V-measure

```
>>> from sklearn.metrics import v_measure_score
>>> metrics.v_measure_score(y_true, y_pred)
```

Cross-Validation

```
>>> from sklearn.cross_validation import cross_val_score
>>> print(cross_val_score(knn, X_train, y_train, cv=4))
>>> print(cross_val_score(lr, X, y, cv=2))
```

Tune Your Model

Grid Search

```
>>> from sklearn.grid_search import GridSearchCV
>>> params = {"n_neighbors": np.arange(1,3),
              "metric": ["euclidean", "cityblock"]}
>>> grid = GridSearchCV(estimator=knn,
                        param_grid=params)
>>> grid.fit(X_train, y_train)
>>> print(grid.best_score_)
>>> print(grid.best_estimator_.n_neighbors)
```

Randomized Parameter Optimization

```
>>> from sklearn.grid_search import RandomizedSearchCV
>>> params = {"n_neighbors": range(1,5),
              "weights": ["uniform", "distance"]}
>>> rsearch = RandomizedSearchCV(estimator=knn,
                                 param_distributions=params,
                                 cv=4,
                                 n_iter=8,
                                 random_state=5)
>>> rsearch.fit(X_train, y_train)
>>> print(rsearch.best_score_)
```

VIP Cheatsheet: Machine Learning Tips

Afshine Amidi and Shervine Amidi

September 9, 2018

Metrics

Given a set of data points $\{x^{(1)}, ..., x^{(m)}\}$, where each $x^{(i)}$ has n features, associated to a set of outcomes $\{y^{(1)}, ..., y^{(m)}\}$, we want to assess a given classifier that learns how to predict y from x.

Classification

In a context of a binary classification, here are the main metrics that are important to track to assess the performance of the model.

❒ **Confusion matrix** – The confusion matrix is used to have a more complete picture when assessing the performance of a model. It is defined as follows:

		Predicted class +	**Predicted** class –
Actual class	+	**TP** True Positives	**FN** False Negatives Type II error
	–	**FP** False Positives Type I error	**TN** True Negatives

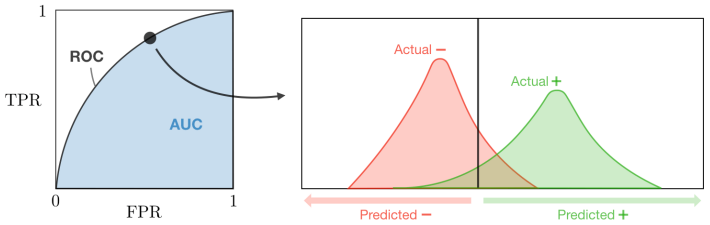
❒ **Main metrics** – The following metrics are commonly used to assess the performance of classification models:

Metric	Formula	Interpretation
Accuracy	$\frac{\text{TP}+\text{TN}}{\text{TP}+\text{TN}+\text{FP}+\text{FN}}$	Overall performance of model
Precision	$\frac{\text{TP}}{\text{TP}+\text{FP}}$	How accurate the positive predictions are
Recall Sensitivity	$\frac{\text{TP}}{\text{TP}+\text{FN}}$	Coverage of actual positive sample
Specificity	$\frac{\text{TN}}{\text{TN}+\text{FP}}$	Coverage of actual negative sample
F1 score	$\frac{2\text{TP}}{2\text{TP}+\text{FP}+\text{FN}}$	Hybrid metric useful for unbalanced classes

❒ **ROC** – The receiver operating curve, also noted ROC, is the plot of TPR versus FPR by varying the threshold. These metrics are are summed up in the table below:

Metric	Formula	Equivalent
True Positive Rate TPR	$\frac{\text{TP}}{\text{TP}+\text{FN}}$	Recall, sensitivity
False Positive Rate FPR	$\frac{\text{FP}}{\text{TN}+\text{FP}}$	1-specificity

❒ **AUC** – The area under the receiving operating curve, also noted AUC or AUROC, is the area below the ROC as shown in the following figure:



Regression

❒ **Basic metrics** – Given a regression model f, the following metrics are commonly used to assess the performance of the model:

Total sum of squares	Explained sum of squares	Residual sum of squares
$\text{SS}_{\text{tot}} = \sum_{i=1}^{m}(y_i - \overline{y})^2$	$\text{SS}_{\text{reg}} = \sum_{i=1}^{m}(f(x_i) - \overline{y})^2$	$\text{SS}_{\text{res}} = \sum_{i=1}^{m}(y_i - f(x_i))^2$

❒ **Coefficient of determination** – The coefficient of determination, often noted R^2 or r^2, provides a measure of how well the observed outcomes are replicated by the model and is defined as follows:

$$R^2 = 1 - \frac{\text{SS}_{\text{res}}}{\text{SS}_{\text{tot}}}$$

❒ **Main metrics** – The following metrics are commonly used to assess the performance of regression models, by taking into account the number of variables n that they take into consideration:

Mallow's Cp	AIC	BIC	Adjusted R^2
$\frac{\text{SS}_{\text{res}} + 2(n+1)\widehat{\sigma}^2}{m}$	$2\big[(n+2) - \log(L)\big]$	$\log(m)(n+2) - 2\log(L)$	$1 - \frac{(1-R^2)(m-1)}{m-n-1}$

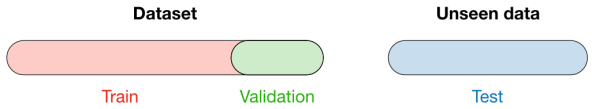
where L is the likelihood and $\widehat{\sigma}^2$ is an estimate of the variance associated with each response.

Model selection

❒ **Vocabulary** – When selecting a model, we distinguish 3 different parts of the data that we have as follows:

Training set	Validation set	Testing set
- Model is trained - Usually 80% of the dataset	- Model is assessed - Usually 20% of the dataset - Also called hold-out or development set	- Model gives predictions - Unseen data

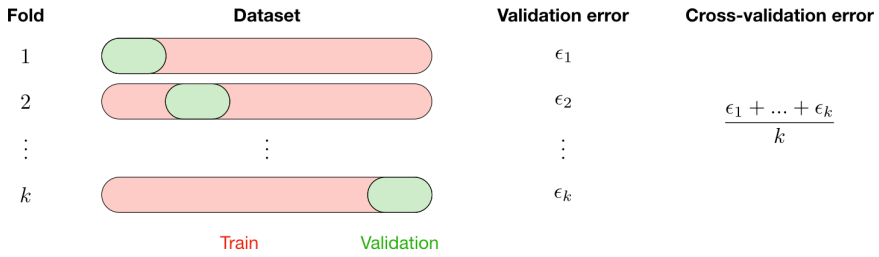
Once the model has been chosen, it is trained on the entire dataset and tested on the unseen test set. These are represented in the figure below:



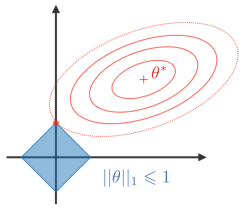
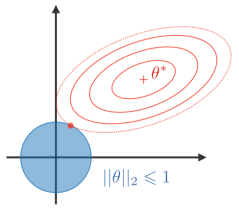
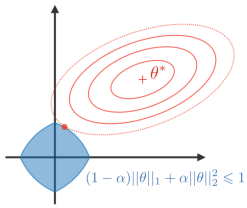
❒ **Cross-validation** – Cross-validation, also noted CV, is a method that is used to select a model that does not rely too much on the initial training set. The different types are summed up in the table below:

k-fold	Leave-p-out
- Training on $k-1$ folds and assessment on the remaining one - Generally $k=5$ or 10	- Training on $n-p$ observations and assessment on the p remaining ones - Case $p=1$ is called leave-one-out

The most commonly used method is called k-fold cross-validation and splits the training data into k folds to validate the model on one fold while training the model on the $k-1$ other folds, all of this k times. The error is then averaged over the k folds and is named cross-validation error.



❒ **Regularization** – The regularization procedure aims at avoiding the model to overfit the data and thus deals with high variance issues. The following table sums up the different types of commonly used regularization techniques:

LASSO	Ridge	Elastic Net
- Shrinks coefficients to 0 - Good for variable selection	Makes coefficients smaller	Tradeoff between variable selection and small coefficients
		
$... + \lambda\|\|\theta\|\|_1$ $\lambda \in \mathbb{R}$	$... + \lambda\|\|\theta\|\|_2^2$ $\lambda \in \mathbb{R}$	$... + \lambda\left[(1-\alpha)\|\|\theta\|\|_1 + \alpha\|\|\theta\|\|_2^2\right]$ $\lambda \in \mathbb{R}$, $\alpha \in [0,1]$

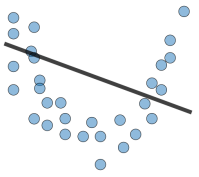
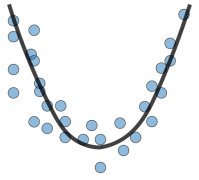
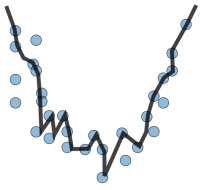
❒ **Model selection** – Train model on training set, then evaluate on the development set, then pick best performance model on the development set, and retrain all of that model on the whole training set.

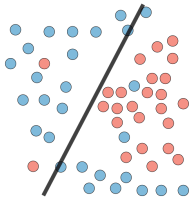
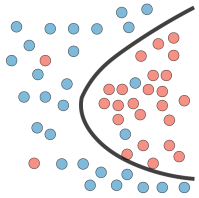
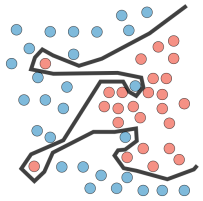
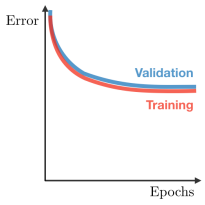
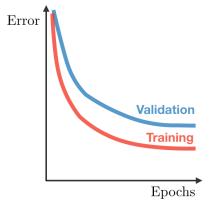
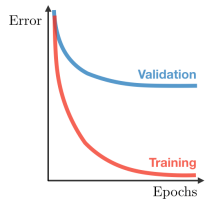
Diagnostics

❒ **Bias** – The bias of a model is the difference between the expected prediction and the correct model that we try to predict for given data points.

❒ **Variance** – The variance of a model is the variability of the model prediction for given data points.

❒ **Bias/variance tradeoff** – The simpler the model, the higher the bias, and the more complex the model, the higher the variance.

	Underfitting	Just right	Overfitting
Symptoms	- High training error - Training error close to test error - High bias	- Training error slightly lower than test error	- Low training error - Training error much lower than test error - High variance
Regression			

Classification			
Deep learning			
Remedies	- Complexify model - Add more features - Train longer		- Regularize - Get more data

❒ **Error analysis** – Error analysis is analyzing the root cause of the difference in performance between the current and the perfect models.

❒ **Ablative analysis** – Ablative analysis is analyzing the root cause of the difference in performance between the current and the baseline models.

VIP Cheatsheet: Supervised Learning

Afshine Amidi and Shervine Amidi

September 9, 2018

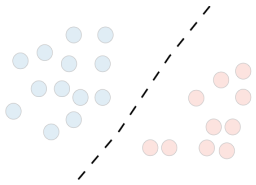
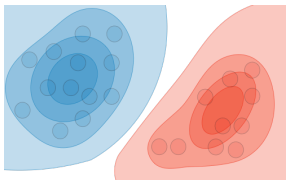
Introduction to Supervised Learning

Given a set of data points $\{x^{(1)}, ..., x^{(m)}\}$ associated to a set of outcomes $\{y^{(1)}, ..., y^{(m)}\}$, we want to build a classifier that learns how to predict y from x.

❒ **Type of prediction** – The different types of predictive models are summed up in the table below:

	Regression	**Classifier**
Outcome	Continuous	Class
Examples	Linear regression	Logistic regression, SVM, Naive Bayes

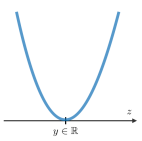
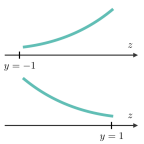
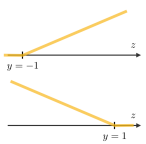
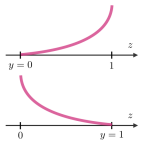
❒ **Type of model** – The different models are summed up in the table below:

	Discriminative model	**Generative model**
Goal	Directly estimate $P(y\|x)$	Estimate $P(x\|y)$ to deduce $P(y\|x)$
What's learned	Decision boundary	Probability distributions of the data
Illustration		
Examples	Regressions, SVMs	GDA, Naive Bayes

Notations and general concepts

❒ **Hypothesis** – The hypothesis is noted h_θ and is the model that we choose. For a given input data $x^{(i)}$, the model prediction output is $h_\theta(x^{(i)})$.

❒ **Loss function** – A loss function is a function $L : (z,y) \in \mathbb{R} \times Y \longmapsto L(z,y) \in \mathbb{R}$ that takes as inputs the predicted value z corresponding to the real data value y and outputs how different they are. The common loss functions are summed up in the table below:

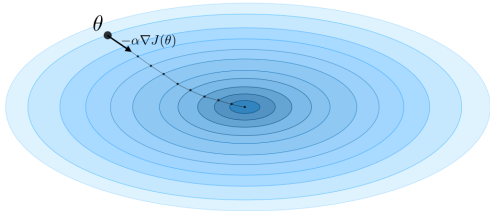
Least squared	**Logistic**	**Hinge**	**Cross-entropy**
$\frac{1}{2}(y-z)^2$	$\log(1+\exp(-yz))$	$\max(0,1-yz)$	$-\left[y\log(z)+(1-y)\log(1-z)\right]$
			
Linear regression	Logistic regression	SVM	Neural Network

❒ **Cost function** – The cost function J is commonly used to assess the performance of a model, and is defined with the loss function L as follows:

$$\boxed{J(\theta) = \sum_{i=1}^{m} L(h_\theta(x^{(i)}), y^{(i)})}$$

❒ **Gradient descent** – By noting $\alpha \in \mathbb{R}$ the learning rate, the update rule for gradient descent is expressed with the learning rate and the cost function J as follows:

$$\boxed{\theta \longleftarrow \theta - \alpha \nabla J(\theta)}$$



Remark: Stochastic gradient descent (SGD) is updating the parameter based on each training example, and batch gradient descent is on a batch of training examples.

❒ **Likelihood** – The likelihood of a model $L(\theta)$ given parameters θ is used to find the optimal parameters θ through maximizing the likelihood. In practice, we use the log-likelihood $\ell(\theta) = \log(L(\theta))$ which is easier to optimize. We have:

$$\boxed{\theta^{\text{opt}} = \underset{\theta}{\arg\max}\ L(\theta)}$$

❒ **Newton's algorithm** – The Newton's algorithm is a numerical method that finds θ such that $\ell'(\theta) = 0$. Its update rule is as follows:

$$\boxed{\theta \leftarrow \theta - \frac{\ell'(\theta)}{\ell''(\theta)}}$$

Remark: the multidimensional generalization, also known as the Newton-Raphson method, has the following update rule:

$$\theta \leftarrow \theta - \left(\nabla^2_\theta \ell(\theta)\right)^{-1} \nabla_\theta \ell(\theta)$$

Linear regression

We assume here that $y|x;\theta \sim \mathcal{N}(\mu,\sigma^2)$

❒ **Normal equations** – By noting X the matrix design, the value of θ that minimizes the cost function is a closed-form solution such that:

$$\boxed{\theta = (X^TX)^{-1}X^Ty}$$

❒ **LMS algorithm** – By noting α the learning rate, the update rule of the Least Mean Squares (LMS) algorithm for a training set of m data points, which is also known as the Widrow-Hoff learning rule, is as follows:

$$\boxed{\forall j, \quad \theta_j \leftarrow \theta_j + \alpha \sum_{i=1}^{m} \left[y^{(i)} - h_\theta(x^{(i)})\right] x_j^{(i)}}$$

Remark: the update rule is a particular case of the gradient ascent.

❒ **LWR** – Locally Weighted Regression, also known as LWR, is a variant of linear regression that weights each training example in its cost function by $w^{(i)}(x)$, which is defined with parameter $\tau \in \mathbb{R}$ as:

$$\boxed{w^{(i)}(x) = \exp\left(-\frac{(x^{(i)}-x)^2}{2\tau^2}\right)}$$

Classification and logistic regression

❒ **Sigmoid function** – The sigmoid function g, also known as the logistic function, is defined as follows:

$$\forall z \in \mathbb{R}, \quad \boxed{g(z) = \frac{1}{1+e^{-z}} \in]0,1[}$$

❒ **Logistic regression** – We assume here that $y|x;\theta \sim \text{Bernoulli}(\phi)$. We have the following form:

$$\boxed{\phi = p(y=1|x;\theta) = \frac{1}{1+\exp(-\theta^Tx)} = g(\theta^Tx)}$$

Remark: there is no closed form solution for the case of logistic regressions.

❒ **Softmax regression** – A softmax regression, also called a multiclass logistic regression, is used to generalize logistic regression when there are more than 2 outcome classes. By convention, we set $\theta_K = 0$, which makes the Bernoulli parameter ϕ_i of each class i equal to:

$$\boxed{\phi_i = \frac{\exp(\theta_i^Tx)}{\sum_{j=1}^{K}\exp(\theta_j^Tx)}}$$

Generalized Linear Models

❒ **Exponential family** – A class of distributions is said to be in the exponential family if it can be written in terms of a natural parameter, also called the canonical parameter or link function, η, a sufficient statistic $T(y)$ and a log-partition function $a(\eta)$ as follows:

$$\boxed{p(y;\eta) = b(y)\exp(\eta T(y) - a(\eta))}$$

Remark: we will often have $T(y) = y$. Also, $\exp(-a(\eta))$ can be seen as a normalization parameter that will make sure that the probabilities sum to one.

Here are the most common exponential distributions summed up in the following table:

Distribution	η	$T(y)$	$a(\eta)$	$b(y)$
Bernoulli	$\log\left(\frac{\phi}{1-\phi}\right)$	y	$\log(1+\exp(\eta))$	1
Gaussian	μ	y	$\frac{\eta^2}{2}$	$\frac{1}{\sqrt{2\pi}}\exp\left(-\frac{y^2}{2}\right)$
Poisson	$\log(\lambda)$	y	e^η	$\frac{1}{y!}$
Geometric	$\log(1-\phi)$	y	$\log\left(\frac{e^\eta}{1-e^\eta}\right)$	1

❒ **Assumptions of GLMs** – Generalized Linear Models (GLM) aim at predicting a random variable y as a function fo $x \in \mathbb{R}^{n+1}$ and rely on the following 3 assumptions:

(1) $\boxed{y|x;\theta \sim \text{ExpFamily}(\eta)}$ (2) $\boxed{h_\theta(x) = E[y|x;\theta]}$ (3) $\boxed{\eta = \theta^Tx}$

Remark: ordinary least squares and logistic regression are special cases of generalized linear models.

Support Vector Machines

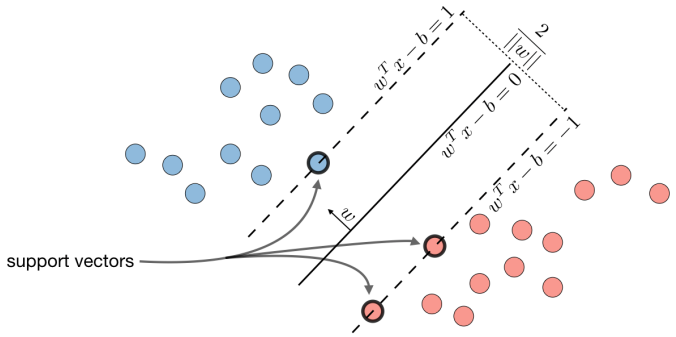
The goal of support vector machines is to find the line that maximizes the minimum distance to the line.

❒ **Optimal margin classifier** – The optimal margin classifier h is such that:

$$\boxed{h(x) = \text{sign}(w^Tx - b)}$$

where $(w,b) \in \mathbb{R}^n \times \mathbb{R}$ is the solution of the following optimization problem:

$$\boxed{\min \frac{1}{2}||w||^2} \quad \text{such that} \quad \boxed{y^{(i)}(w^Tx^{(i)} - b) \geqslant 1}$$



Remark: the line is defined as $\boxed{w^T x - b = 0}$.

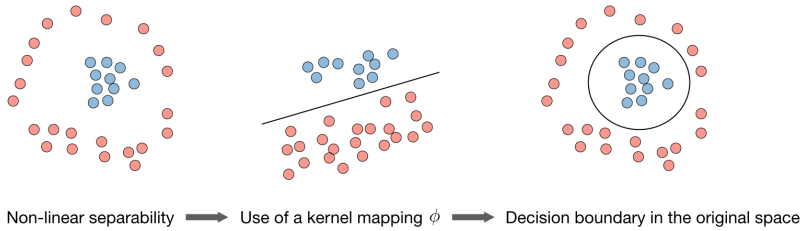
❒ **Hinge loss** – The hinge loss is used in the setting of SVMs and is defined as follows:

$$\boxed{L(z,y) = [1-yz]_+ = \max(0,1-yz)}$$

❒ **Kernel** – Given a feature mapping ϕ, we define the kernel K to be defined as:

$$\boxed{K(x,z) = \phi(x)^T\phi(z)}$$

In practice, the kernel K defined by $K(x,z) = \exp\left(-\frac{||x-z||^2}{2\sigma^2}\right)$ is called the Gaussian kernel and is commonly used.



Remark: we say that we use the "kernel trick" to compute the cost function using the kernel because we actually don't need to know the explicit mapping ϕ, which is often very complicated. Instead, only the values $K(x,z)$ are needed.

❒ **Lagrangian** – We define the Lagrangian $\mathcal{L}(w,b)$ as follows:

$$\boxed{\mathcal{L}(w,b) = f(w) + \sum_{i=1}^{l}\beta_i h_i(w)}$$

Remark: the coefficients β_i are called the Lagrange multipliers.

Generative Learning

A generative model first tries to learn how the data is generated by estimating $P(x|y)$, which we can then use to estimate $P(y|x)$ by using Bayes' rule.

Gaussian Discriminant Analysis

❒ **Setting** – The Gaussian Discriminant Analysis assumes that y and $x|y=0$ and $x|y=1$ are such that:

$$\boxed{y \sim \text{Bernoulli}(\phi)}$$

$$\boxed{x|y=0 \sim \mathcal{N}(\mu_0,\Sigma)} \quad \text{and} \quad \boxed{x|y=1 \sim \mathcal{N}(\mu_1,\Sigma)}$$

❒ **Estimation** – The following table sums up the estimates that we find when maximizing the likelihood:

$\widehat{\phi}$	$\widehat{\mu_j}$ $(j=0,1)$	$\widehat{\Sigma}$
$\frac{1}{m}\sum_{i=1}^{m} 1_{\{y^{(i)}=1\}}$	$\frac{\sum_{i=1}^{m} 1_{\{y^{(i)}=j\}} x^{(i)}}{\sum_{i=1}^{m} 1_{\{y^{(i)}=j\}}}$	$\frac{1}{m}\sum_{i=1}^{m}(x^{(i)}-\mu_{y^{(i)}})(x^{(i)}-\mu_{y^{(i)}})^T$

Naive Bayes

❒ **Assumption** – The Naive Bayes model supposes that the features of each data point are all independent:

$$\boxed{P(x|y) = P(x_1,x_2,...|y) = P(x_1|y)P(x_2|y)... = \prod_{i=1}^{n} P(x_i|y)}$$

❒ **Solutions** – Maximizing the log-likelihood gives the following solutions, with $k \in \{0,1\}$, $l \in [\![1,L]\!]$

$$\boxed{P(y=k) = \frac{1}{m} \times \#\{j|y^{(j)}=k\}} \quad \text{and} \quad \boxed{P(x_i=l|y=k) = \frac{\#\{j|y^{(j)}=k \text{ and } x_i^{(j)}=l\}}{\#\{j|y^{(j)}=k\}}}$$

Remark: Naive Bayes is widely used for text classification and spam detection.

Tree-based and ensemble methods

These methods can be used for both regression and classification problems.

❒ **CART** – Classification and Regression Trees (CART), commonly known as decision trees, can be represented as binary trees. They have the advantage to be very interpretable.

❒ **Random forest** – It is a tree-based technique that uses a high number of decision trees built out of randomly selected sets of features. Contrary to the simple decision tree, it is highly uninterpretable but its generally good performance makes it a popular algorithm.

Remark: random forests are a type of ensemble methods.

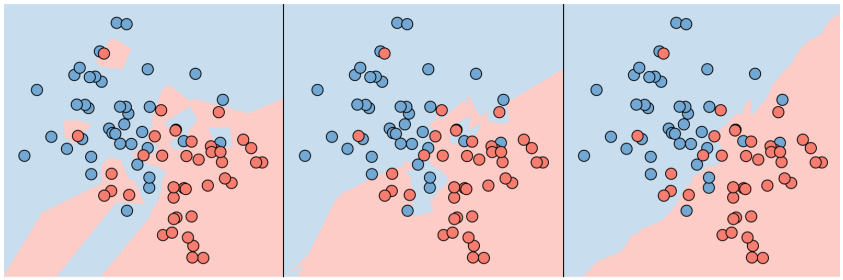
❒ **Boosting** – The idea of boosting methods is to combine several weak learners to form a stronger one. The main ones are summed up in the table below:

Adaptive boosting	Gradient boosting
- High weights are put on errors to improve at the next boosting step - Known as Adaboost	- Weak learners trained on remaining errors

Other non-parametric approaches

❒ **k-nearest neighbors** – The k-nearest neighbors algorithm, commonly known as k-NN, is a non-parametric approach where the response of a data point is determined by the nature of its k neighbors from the training set. It can be used in both classification and regression settings.

Remark: The higher the parameter k, the higher the bias, and the lower the parameter k, the higher the variance.

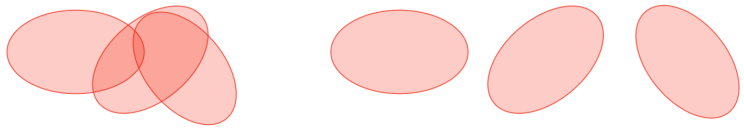


$k=1$ $k=3$ $k=11$

Learning Theory

❒ **Union bound** – Let $A_1, ..., A_k$ be k events. We have:

$$\boxed{P(A_1 \cup ... \cup A_k) \leqslant P(A_1) + ... + P(A_k)}$$



$A_1 \cup A_2 \cup A_3$ A_1 A_2 A_3

❒ **Hoeffding inequality** – Let $Z_1, .., Z_m$ be m iid variables drawn from a Bernoulli distribution of parameter ϕ. Let $\widehat{\phi}$ be their sample mean and $\gamma > 0$ fixed. We have:

$$\boxed{P(|\phi - \widehat{\phi}| > \gamma) \leqslant 2\exp(-2\gamma^2 m)}$$

Remark: this inequality is also known as the Chernoff bound.

❒ **Training error** – For a given classifier h, we define the training error $\widehat{\epsilon}(h)$, also known as the empirical risk or empirical error, to be as follows:

$$\boxed{\widehat{\epsilon}(h) = \frac{1}{m}\sum_{i=1}^{m} 1_{\{h(x^{(i)}) \neq y^{(i)}\}}}$$

❒ **Probably Approximately Correct (PAC)** – PAC is a framework under which numerous results on learning theory were proved, and has the following set of assumptions:

- the training and testing sets follow the same distribution
- the training examples are drawn independently

❒ **Shattering** – Given a set $S = \{x^{(1)}, ..., x^{(d)}\}$, and a set of classifiers $\mathcal{H}$, we say that $\mathcal{H}$ shatters S if for any set of labels $\{y^{(1)}, ..., y^{(d)}\}$, we have:

$$\boxed{\exists h \in \mathcal{H}, \quad \forall i \in [\![1,d]\!], \quad h(x^{(i)}) = y^{(i)}}$$

❒ **Upper bound theorem** – Let $\mathcal{H}$ be a finite hypothesis class such that $|\mathcal{H}| = k$ and let δ and the sample size m be fixed. Then, with probability of at least $1-\delta$, we have:

$$\boxed{\epsilon(\widehat{h}) \leqslant \left(\min_{h \in \mathcal{H}} \epsilon(h)\right) + 2\sqrt{\frac{1}{2m}\log\left(\frac{2k}{\delta}\right)}}$$

❒ **VC dimension** – The Vapnik-Chervonenkis (VC) dimension of a given infinite hypothesis class $\mathcal{H}$, noted $\text{VC}(\mathcal{H})$ is the size of the largest set that is shattered by $\mathcal{H}$.

Remark: the VC dimension of $\mathcal{H} = \{$set of linear classifiers in 2 dimensions$\}$ is 3.

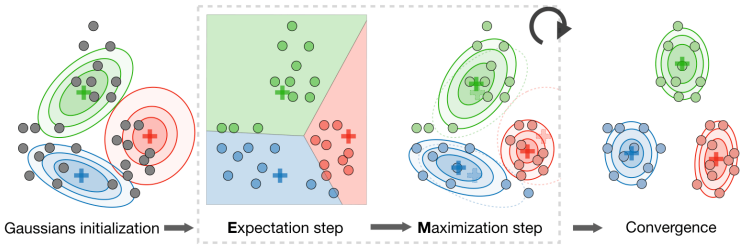
❒ **Theorem (Vapnik)** – Let $\mathcal{H}$ be given, with $\text{VC}(\mathcal{H}) = d$ and m the number of training examples. With probability at least $1-\delta$, we have:

$$\boxed{\epsilon(\widehat{h}) \leqslant \left(\min_{h \in \mathcal{H}} \epsilon(h)\right) + O\left(\sqrt{\frac{d}{m}\log\left(\frac{m}{d}\right) + \frac{1}{m}\log\left(\frac{1}{\delta}\right)}\right)}$$

VIP Cheatsheet: Unsupervised Learning

Afshine Amidi and Shervine Amidi

September 9, 2018



Introduction to Unsupervised Learning

❒ **Motivation** – The goal of unsupervised learning is to find hidden patterns in unlabeled data $\{x^{(1)},...,x^{(m)}\}$.

❒ **Jensen's inequality** – Let f be a convex function and X a random variable. We have the following inequality:

$$\boxed{E[f(X)] \geqslant f(E[X])}$$

Expectation-Maximization

❒ **Latent variables** – Latent variables are hidden/unobserved variables that make estimation problems difficult, and are often denoted z. Here are the most common settings where there are latent variables:

Setting	Latent variable z	$x\|z$	Comments
Mixture of k Gaussians	Multinomial(ϕ)	$\mathcal{N}(\mu_j,\Sigma_j)$	$\mu_j \in \mathbb{R}^n, \phi \in \mathbb{R}^k$
Factor analysis	$\mathcal{N}(0,I)$	$\mathcal{N}(\mu+\Lambda z,\psi)$	$\mu_j \in \mathbb{R}^n$

❒ **Algorithm** – The Expectation-Maximization (EM) algorithm gives an efficient method at estimating the parameter θ through maximum likelihood estimation by repeatedly constructing a lower-bound on the likelihood (E-step) and optimizing that lower bound (M-step) as follows:

- E-step: Evaluate the posterior probability $Q_i(z^{(i)})$ that each data point $x^{(i)}$ came from a particular cluster $z^{(i)}$ as follows:

$$\boxed{Q_i(z^{(i)}) = P(z^{(i)}|x^{(i)};\theta)}$$

- M-step: Use the posterior probabilities $Q_i(z^{(i)})$ as cluster specific weights on data points $x^{(i)}$ to separately re-estimate each cluster model as follows:

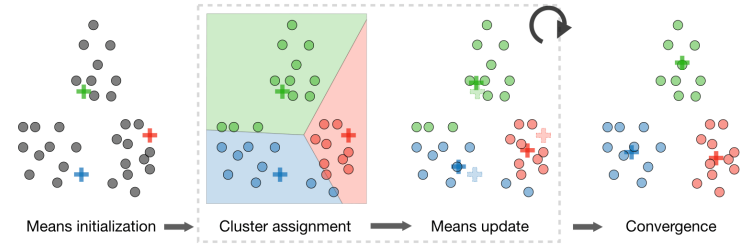
$$\boxed{\theta_i = \underset{\theta}{\text{argmax}} \sum_i \int_{z^{(i)}} Q_i(z^{(i)}) \log\left(\frac{P(x^{(i)},z^{(i)};\theta)}{Q_i(z^{(i)})}\right) dz^{(i)}}$$

k-means clustering

We note $c^{(i)}$ the cluster of data point i and μ_j the center of cluster j.

❒ **Algorithm** – After randomly initializing the cluster centroids $\mu_1,\mu_2,...,\mu_k \in \mathbb{R}^n$, the k-means algorithm repeats the following step until convergence:

$$\boxed{c^{(i)} = \underset{j}{\arg\min}||x^{(i)}-\mu_j||^2} \quad \text{and} \quad \boxed{\mu_j = \frac{\sum_{i=1}^m 1_{\{c^{(i)}=j\}} x^{(i)}}{\sum_{i=1}^m 1_{\{c^{(i)}=j\}}}}$$



❒ **Distortion function** – In order to see if the algorithm converges, we look at the distortion function defined as follows:

$$\boxed{J(c,\mu) = \sum_{i=1}^m ||x^{(i)}-\mu_{c^{(i)}}||^2}$$

Hierarchical clustering

❒ **Algorithm** – It is a clustering algorithm with an agglomerative hierarchical approach that build nested clusters in a successive manner.

❒ **Types** – There are different sorts of hierarchical clustering algorithms that aims at optimizing different objective functions, which is summed up in the table below:

Ward linkage	Average linkage	Complete linkage
Minimize within cluster distance	Minimize average distance between cluster pairs	Minimize maximum distance of between cluster pairs

Clustering assessment metrics

In an unsupervised learning setting, it is often hard to assess the performance of a model since we don't have the ground truth labels as was the case in the supervised learning setting.

❒ **Silhouette coefficient** – By noting a and b the mean distance between a sample and all other points in the same class, and between a sample and all other points in the next nearest cluster, the silhouette coefficient s for a single sample is defined as follows:

$$\boxed{s = \frac{b-a}{\max(a,b)}}$$

❒ **Calinski-Harabaz index** – By noting k the number of clusters, B_k and W_k the between and within-clustering dispersion matrices respectively defined as

$$B_k = \sum_{j=1}^{k} n_{c^{(i)}} (\mu_{c^{(i)}} - \mu)(\mu_{c^{(i)}} - \mu)^T, \qquad W_k = \sum_{i=1}^{m} (x^{(i)} - \mu_{c^{(i)}})(x^{(i)} - \mu_{c^{(i)}})^T$$

the Calinski-Harabaz index $s(k)$ indicates how well a clustering model defines its clusters, such that the higher the score, the more dense and well separated the clusters are. It is defined as follows:

$$\boxed{s(k) = \frac{\text{Tr}(B_k)}{\text{Tr}(W_k)} \times \frac{N-k}{k-1}}$$

Principal component analysis

It is a dimension reduction technique that finds the variance maximizing directions onto which to project the data.

❒ **Eigenvalue, eigenvector** – Given a matrix $A \in \mathbb{R}^{n \times n}$, λ is said to be an eigenvalue of A if there exists a vector $z \in \mathbb{R}^n \backslash \{0\}$, called eigenvector, such that we have:

$$\boxed{Az = \lambda z}$$

❒ **Spectral theorem** – Let $A \in \mathbb{R}^{n \times n}$. If A is symmetric, then A is diagonalizable by a real orthogonal matrix $U \in \mathbb{R}^{n \times n}$. By noting $\Lambda = \text{diag}(\lambda_1, ..., \lambda_n)$, we have:

$$\boxed{\exists \Lambda \text{ diagonal}, \quad A = U \Lambda U^T}$$

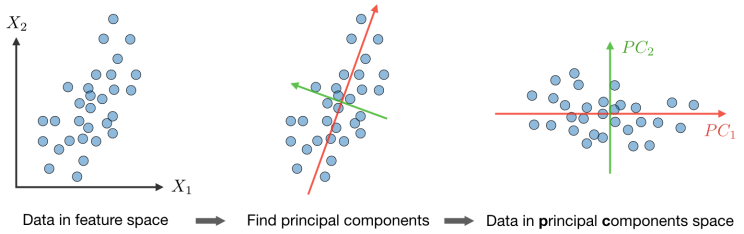
Remark: the eigenvector associated with the largest eigenvalue is called principal eigenvector of matrix A.

❒ **Algorithm** – The Principal Component Analysis (PCA) procedure is a dimension reduction technique that projects the data on k dimensions by maximizing the variance of the data as follows:

- Step 1: Normalize the data to have a mean of 0 and standard deviation of 1.

$$\boxed{x_j^{(i)} \leftarrow \frac{x_j^{(i)} - \mu_j}{\sigma_j}} \quad \text{where} \quad \boxed{\mu_j = \frac{1}{m} \sum_{i=1}^{m} x_j^{(i)}} \quad \text{and} \quad \boxed{\sigma_j^2 = \frac{1}{m} \sum_{i=1}^{m} (x_j^{(i)} - \mu_j)^2}$$

- Step 2: Compute $\Sigma = \frac{1}{m} \sum_{i=1}^{m} x^{(i)} x^{(i)^T} \in \mathbb{R}^{n \times n}$, which is symmetric with real eigenvalues.
- Step 3: Compute $u_1, ..., u_k \in \mathbb{R}^n$ the k orthogonal principal eigenvectors of Σ, i.e. the orthogonal eigenvectors of the k largest eigenvalues.
- Step 4: Project the data on $\text{span}_{\mathbb{R}}(u_1, ..., u_k)$. This procedure maximizes the variance among all k-dimensional spaces.



Independent component analysis

It is a technique meant to find the underlying generating sources.

❒ **Assumptions** – We assume that our data x has been generated by the n-dimensional source vector $s = (s_1, ..., s_n)$, where s_i are independent random variables, via a mixing and non-singular matrix A as follows:

$$\boxed{x = As}$$

The goal is to find the unmixing matrix $W = A^{-1}$ by an update rule.

❒ **Bell and Sejnowski ICA algorithm** – This algorithm finds the unmixing matrix W by following the steps below:

- Write the probability of $x = As = W^{-1}s$ as:

$$p(x) = \prod_{i=1}^{n} p_s(w_i^T x) \cdot |W|$$

- Write the log likelihood given our training data $\{x^{(i)}, i \in [\![1, m]\!]\}$ and by noting g the sigmoid function as:

$$l(W) = \sum_{i=1}^{m} \left(\sum_{j=1}^{n} \log \left(g'(w_j^T x^{(i)}) \right) + \log |W| \right)$$

Therefore, the stochastic gradient ascent learning rule is such that for each training example $x^{(i)}$, we update W as follows:

$$\boxed{W \longleftarrow W + \alpha \left(\begin{pmatrix} 1 - 2g(w_1^T x^{(i)}) \\ 1 - 2g(w_2^T x^{(i)}) \\ \vdots \\ 1 - 2g(w_n^T x^{(i)}) \end{pmatrix} x^{(i)^T} + (W^T)^{-1} \right)}$$

Python For Data Science *Cheat Sheet*

Keras

Learn Python for data science Interactively at www.DataCamp.com

Keras

Keras is a powerful and easy-to-use deep learning library for Theano and TensorFlow that provides a high-level neural networks API to develop and evaluate deep learning models.

A Basic Example

```
>>> import numpy as np
>>> from keras.models import Sequential
>>> from keras.layers import Dense
>>> data = np.random.random((1000,100))
>>> labels = np.random.randint(2,size=(1000,1))
>>> model = Sequential()
>>> model.add(Dense(32,
                    activation='relu',
                    input_dim=100))
>>> model.add(Dense(1, activation='sigmoid'))
>>> model.compile(optimizer='rmsprop',
                  loss='binary_crossentropy',
                  metrics=['accuracy'])
>>> model.fit(data,labels,epochs=10,batch_size=32)
>>> predictions = model.predict(data)
```

Data

Also see NumPy, Pandas & Scikit-Learn

Your data needs to be stored as NumPy arrays or as a list of NumPy arrays. Ideally, you split the data in training and test sets, for which you can also resort to the `train_test_split` module of `sklearn.cross_validation`.

Keras Data Sets

```
>>> from keras.datasets import boston_housing,
                               mnist,
                               cifar10,
                               imdb
>>> (x_train,y_train),(x_test,y_test) = mnist.load_data()
>>> (x_train2,y_train2),(x_test2,y_test2) = boston_housing.load_data()
>>> (x_train3,y_train3),(x_test3,y_test3) = cifar10.load_data()
>>> (x_train4,y_train4),(x_test4,y_test4) = imdb.load_data(num_words=20000)
>>> num_classes = 10
```

Other

```
>>> from urllib.request import urlopen
>>> data = np.loadtxt(urlopen("http://archive.ics.uci.edu/
ml/machine-learning-databases/pima-indians-diabetes/
pima-indians-diabetes.data"),delimiter=",")
>>> X = data[:,0:8]
>>> y = data [:,8]
```

Model Architecture

Sequential Model

```
>>> from keras.models import Sequential
>>> model = Sequential()
>>> model2 = Sequential()
>>> model3 = Sequential()
```

Multilayer Perceptron (MLP)

Binary Classification

```
>>> from keras.layers import Dense
>>> model.add(Dense(12,
                    input_dim=8,
                    kernel_initializer='uniform',
                    activation='relu'))
>>> model.add(Dense(8,kernel_initializer='uniform',activation='relu'))
>>> model.add(Dense(1,kernel_initializer='uniform',activation='sigmoid'))
```

Multi-Class Classification

```
>>> from keras.layers import Dropout
>>> model.add(Dense(512,activation='relu',input_shape=(784,)))
>>> model.add(Dropout(0.2))
>>> model.add(Dense(512,activation='relu'))
>>> model.add(Dropout(0.2))
>>> model.add(Dense(10,activation='softmax'))
```

Regression

```
>>> model.add(Dense(64,activation='relu',input_dim=train_data.shape[1]))
>>> model.add(Dense(1))
```

Convolutional Neural Network (CNN)

```
>>> from keras.layers import Activation,Conv2D,MaxPooling2D,Flatten
>>> model2.add(Conv2D(32,(3,3),padding='same',input_shape=x_train.shape[1:]))
>>> model2.add(Activation('relu'))
>>> model2.add(Conv2D(32,(3,3)))
>>> model2.add(Activation('relu'))
>>> model2.add(MaxPooling2D(pool_size=(2,2)))
>>> model2.add(Dropout(0.25))

>>> model2.add(Conv2D(64,(3,3), padding='same'))
>>> model2.add(Activation('relu'))
>>> model2.add(Conv2D(64,(3, 3)))
>>> model2.add(Activation('relu'))
>>> model2.add(MaxPooling2D(pool_size=(2,2)))
>>> model2.add(Dropout(0.25))

>>> model2.add(Flatten())
>>> model2.add(Dense(512))
>>> model2.add(Activation('relu'))
>>> model2.add(Dropout(0.5))
>>> model2.add(Dense(num_classes))
>>> model2.add(Activation('softmax'))
```

Recurrent Neural Network (RNN)

```
>>> from keras.klayers import Embedding,LSTM
>>> model3.add(Embedding(20000,128))
>>> model3.add(LSTM(128,dropout=0.2,recurrent_dropout=0.2))
>>> model3.add(Dense(1,activation='sigmoid'))
```

Inspect Model

```
>>> model.output_shape
>>> model.summary()
>>> model.get_config()
>>> model.get_weights()
```

Model output shape
Model summary representation
Model configuration
List all weight tensors in the model

Compile Model

MLP: Binary Classification

```
>>> model.compile(optimizer='adam',
                  loss='binary_crossentropy',
                  metrics=['accuracy'])
```

MLP: Multi-Class Classification

```
>>> model.compile(optimizer='rmsprop',
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])
```

MLP: Regression

```
>>> model.compile(optimizer='rmsprop',
                  loss='mse',
                  metrics=['mae'])
```

Recurrent Neural Network

```
>>> model3.compile(loss='binary_crossentropy',
                   optimizer='adam',
                   metrics=['accuracy'])
```

Model Training

```
>>> model3.fit(x_train4,
               y_train4,
               batch_size=32,
               epochs=15,
               verbose=1,
               validation_data=(x_test4,y_test4))
```

Evaluate Your Model's Performance

```
>>> score = model3.evaluate(x_test,
                            y_test,
                            batch_size=32)
```

Prediction

```
>>> model3.predict(x_test4, batch_size=32)
>>> model3.predict_classes(x_test4,batch_size=32)
```

Save/ Reload Models

```
>>> from keras.models import load_model
>>> model3.save('model_file.h5')
>>> my_model = load_model('my_model.h5')
```

Model Fine-tuning

Optimization Parameters

```
>>> from keras.optimizers import RMSprop
>>> opt = RMSprop(lr=0.0001, decay=1e-6)
>>> model2.compile(loss='categorical_crossentropy',
                   optimizer=opt,
                   metrics=['accuracy'])
```

Early Stopping

```
>>> from keras.callbacks import EarlyStopping
>>> early_stopping_monitor = EarlyStopping(patience=2)
>>> model3.fit(x_train4,
               y_train4,
               batch_size=32,
               epochs=15,
               validation_data=(x_test4,y_test4),
               callbacks=[early_stopping_monitor])
```

Preprocessing

Also see NumPy & Scikit-Learn

Sequence Padding

```
>>> from keras.preprocessing import sequence
>>> x_train4 = sequence.pad_sequences(x_train4,maxlen=80)
>>> x_test4 = sequence.pad_sequences(x_test4,maxlen=80)
```

One-Hot Encoding

```
>>> from keras.utils import to_categorical
>>> Y_train = to_categorical(y_train, num_classes)
>>> Y_test = to_categorical(y_test, num_classes)
>>> Y_train3 = to_categorical(y_train3, num_classes)
>>> Y_test3 = to_categorical(y_test3, num_classes)
```

Train and Test Sets

```
>>> from sklearn.model_selection import train_test_split
>>> X_train5,X_test5,y_train5,y_test5 = train_test_split(X,
                                                         y,
                                                         test_size=0.33,
                                                         random_state=42)
```

Standardization/Normalization

```
>>> from sklearn.preprocessing import StandardScaler
>>> scaler = StandardScaler().fit(x_train2)
>>> standardized_X = scaler.transform(x_train2)
>>> standardized_X_test = scaler.transform(x_test2)
```

TensorFlow v2.0 Cheat Sheet

ALTOROS

TensorFlow™

TensorFlow is an open-source software library for high-performance numerical computation. Its flexible architecture enables to easily deploy computation across a variety of platforms (CPUs, GPUs, and TPUs), as well as mobile and edge devices, desktops, and clusters of servers. TensorFlow comes with strong support for machine learning and deep learning.

High-Level APIs for Deep Learning

Keras is a handy high-level API standard for deep learning models widely adopted for fast prototyping and state-of-the-art research. It was originally designed to run on top of different low-level computational frameworks and therefore the TensorFlow platform fully implements it.

The Sequential API is the most common way to define your neural network model. It corresponds to the mental image we use when thinking about deep learning: a sequence of layers.

```
import tensorflow as tf
from tensorflow.keras import datasets, layers, models

# Load data set
mnist = datasets.mnist
(x_train, y_train), (x_test, y_test) = mnist.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0

# Construct a neural network model
model = models.Sequential()
model.add(layers.Flatten(input_shape=(28, 28)))
model.add(layers.Dense(512, activation=tf.nn.relu))
model.add(layers.Dropout(0.2))
model.add(layers.Dense(10, activation=tf.nn.softmax))
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

# Train and evaluate the model
model.fit(x_train, y_train, epochs=5)
model.evaluate(x_test, y_test)
```

The Functional API enables engineers to define complex topologies, including multi-input and multi-output models, as well as advanced models with shared layers and models with residual connections.

```
from tensorflow.keras.layers import Flatten, Dense, Dropout
from tensorflow.keras.models import Model

# Loading data set must be here <...>

inputs = tf.keras.Input(shape=(28, 28))
x = Flatten()(inputs)
x = Dense(512, activation='relu')(x)
x = Dropout(0.2)(x)
predictions = Dense(10, activation='softmax')(x)
model = Model(inputs=inputs, outputs=predictions)

# Compile, train and evaluate the model here <...>
```

A layer instance is called on a tensor and returns a tensor. An input tensor and output tensor can then be used to define a `Model`, which is compiled and trained just as a `Sequential` model. Models are callable by themselves and can be stacked the same way while reusing trained weights.

Transfer learning and fine-tuning of pretrained models saves your time if your data set does not differ significantly from the original one.

```
import tensorflow as tf
import tensorflow_datasets as tfds

dataset = tfds.load(name='tf_flowers', as_supervised=True)
NUMBER_OF_CLASSES_IN_DATASET = 5
IMG_SIZE = 160

def preprocess_example(image, label):
   image = tf.cast(image, tf.float32)
   image = (image / 127.5) - 1
   image = tf.image.resize(image, (IMG_SIZE, IMG_SIZE))
   return image, label

DATASET_SIZE = 3670
BATCH_SIZE = 32
train = dataset['train'].map(preprocess_example)
train_batches = train.shuffle(DATASET_SIZE).batch(BATCH_SIZE)

# Load MobileNetV2 model pretrained on ImageNet data
model = tf.keras.applications.MobileNetV2(
    input_shape=(IMG_SIZE, IMG_SIZE, 3),
    include_top=False, weights='imagenet', pooling='avg')
model.trainable = False

# Add a new layer for multiclass classification
new_output = tf.keras.layers.Dense(
    NUMBER_OF_CLASSES_IN_DATASET, activation='softmax')
new_model = tf.keras.Sequential([model, new_output])
new_model.compile(
    loss=tf.keras.losses.categorical_crossentropy,
    optimizer=tf.keras.optimizers.RMSprop(lr=1e-3),
    metrics=['accuracy'])

# Train the classification layer
new_model.fit(train_batches.repeat(), epochs=10,
              steps_per_epoch=DATASET_SIZE // BATCH_SIZE)
```

After the execution of the given transfer learning code, you can make MobileNetV2 layers trainable and perform fine-tuning of the resulting model to achieve better results.

Jupyter Notebook

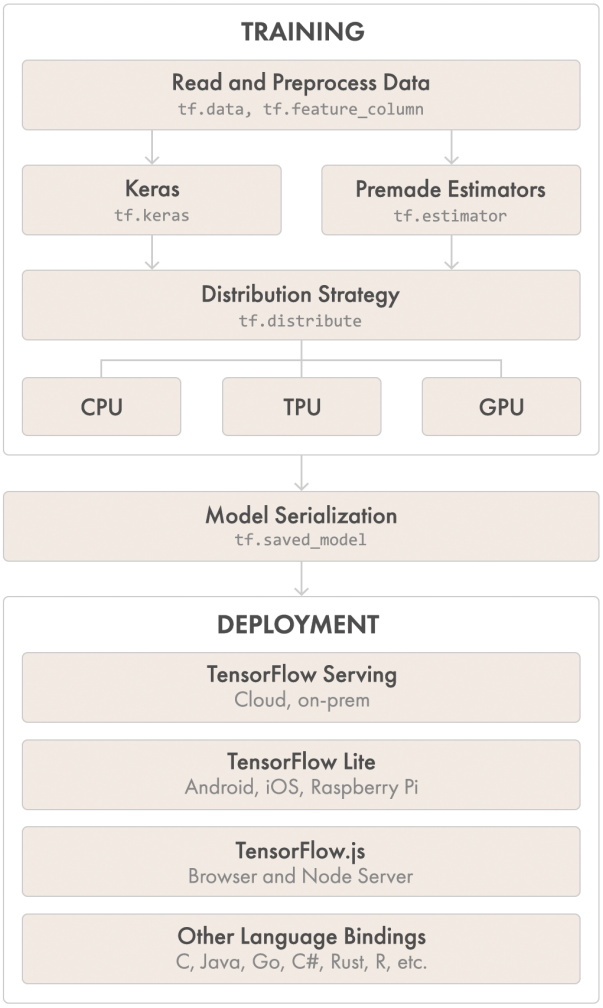
Jupyter Notebook is a web-based interactive computational environment for data science and scientific computing.

Google Colaboratory is a free notebook environment that requires no setup and runs entirely in the cloud. Use it for jump-starting a machine learning project.

TensorFlow v2.0 Cheat Sheet

A Reference Machine Learning Workflow

Here's a conceptual diagram and a workflow example:



01 Load the training data using pipelines created with `tf.data`. As an input, you can use either in-memory data (NumPy), or a local storage, or a remote persistent storage.

02 Build, train, and validate a model with `tf.keras`, or use premade estimators.

03 Run and debug with eager execution, then use `tf.function` for the benefits of graphs.

04 For large ML training tasks, use the Distribution Strategy API for deploying training on Kubernetes clusters within on-premises or cloud environments.

05 Export to SavedModel—an interchange format for TensorFlow Serving, TensorFlow Lite, TensorFlow.js, etc.

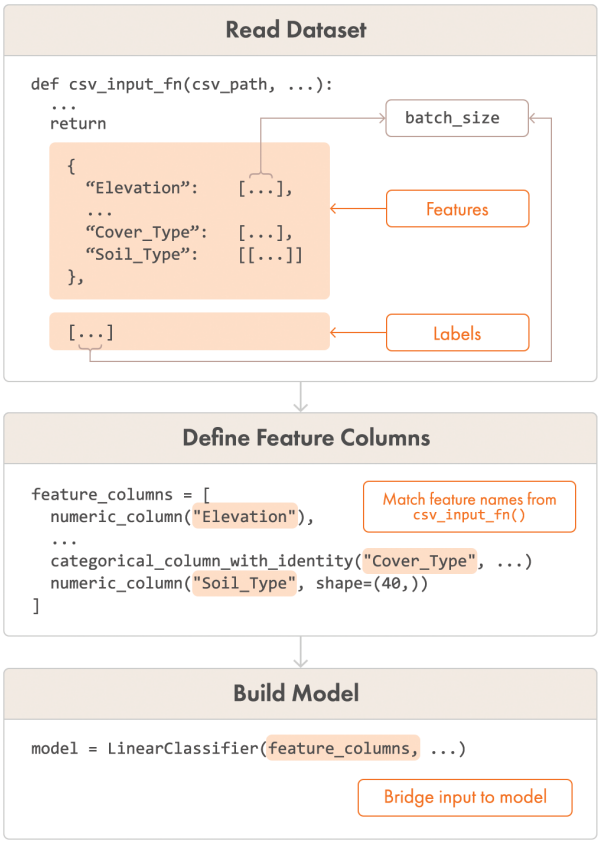
The `tf.data API` enables to build complex input pipelines from simple pieces. The pipeline aggregates data from a distributed file system, applies transformation to each object, and merges shuffled examples into training batches.

`tf.data.Dataset` represents a sequence of elements each containing one or more Tensor object(-s). This can be exemplified by a pair of tensors representing an image and a corresponding class label.

```
import tensorflow as tf

DATASET_URL = “https://archive.ics.uci.edu/ml/machine-” \
              “learning-databases/covtype/covtype.data.gz”
DATASET_SIZE = 387698
dataset_path = tf.keras.utils.get_file(
  fname=DATASET_URL.split(’/’)[-1], origin=DATASET_URL)

COLUMN_NAMES = [
  ’Elevation’, ’Aspect’, ’Slope’,
  ’Horizontal_Distance_To_Hydrology’,
  ’Vertical_Distance_To_Hydrology’,
  ’Horizontal_Distance_To_Roadways’,
  ’Hillshade_9am’, ’Hillshade_Noon’, ’Hillshade_3pm’,
  ’Horizontal_Distance_To_Fire_Points’, ’Soil_Type’,
  ’Cover_Type’]

def _parse_line(line):

  # Decode the line into values
  fields = tf.io.decode_csv(
    records=line, record_defaults=[0.0] * 54 + [0])

  # Pack the result into a dictionary
  features = dict(zip(COLUMN_NAMES,
    fields[:10] + [tf.stack(fields[14:54])] + [fields[-1]]))

  # Extract one-hot encoded class label from the features
  class_label = tf.argmax(fields[10:14], axis=0)
  return features, class_label

def csv_input_fn(csv_path, test=False,
                 batch_size=DATASET_SIZE // 1000):

  # Create a dataset containing the csv lines
  dataset = tf.data.TextLineDataset(filenames=csv_path,
                                    compression_type=’GZIP’)
  # Parse each line
  dataset = dataset.map(_parse_line)

  # Shuffle, repeat, batch the examples for train and test
  dataset = dataset.shuffle(buffer_size=DATASET_SIZE,
                            seed=42)

  TEST_SIZE = DATASET_SIZE // 10
  return dataset.take(TEST_SIZE).batch(TEST_SIZE) if test \
    else dataset.skip(TEST_SIZE).repeat().batch(batch_size)
```

Functions from the `tf.feature_column` namespace are used to put raw data into a TensorFlow data set. A feature column is a high-level configuration abstraction for ingesting and representing features. It does not contain any data but tells the model how to transform the raw data so that it matches the expectation. The exact feature column to choose depends on the feature type and the model type. The continuous feature type is handled by `numeric_column` and can be directly fed into a neural network or a linear model.

TensorFlow v2.0 Cheat Sheet



Categorical features can be ingested by functions with the "`categorical_column_`" prefix, but they need to be wrapped by `embedding_column` or `indicator_column` before being fed into Neural Network models. For linear models, `indicator_column` is an internal representation when categorical columns are passed in directly.

```
feature_columns = [tf.feature_column.numeric_column(name)
                   for name in COLUMN_NAMES[:10]]

feature_columns.append(
  tf.feature_column.categorical_column_with_identity(
    'Cover_Type', num_buckets=8)
)
# Soil_type[1-40] is a tensor of length 40
feature_columns.append(
  tf.feature_column.numeric_column('Soil_Type', shape=(40,))
)
```

The Estimator API provides high-level encapsulation for best practices: model training, evaluation, prediction, and export for serving. The `tf.estimator.Estimator` subclass represents a complete model. Its object creates and manages `tf.Graph` and `tf.Session` for you. Premade estimators include Linear Classifier, DNN Classifier, and Gradient Boosted Trees. `BaselineClassifier` and `BaselineRegressor` will help to establish a simple model for sanity check during further model development.

```
# Build, train, and evaluate the estimator
model = tf.estimator.LinearClassifier(feature_columns,
                                      n_classes=4)
model.train(input_fn=lambda: csv_input_fn(dataset_path),
            steps=10000)
model.ev aluate(
  input_fn=lambda: csv_input_fn(dataset_path, test=True))
```

SavedModel contains a complete TF program and does not require the original model-building code to run, which makes it useful for deploying and sharing models.

```
# Export model to SavedModel
_builder = tf.estimator.export. \
  build_parsing_serving_input_receiver_fn
_spec_maker = tf.feature_column.make_parse_example_spec

serving_input_fn = _builder(_spec_maker(feature_columns))

export_path = model.export_saved_model(
  "/tmp/from_estimator/", serving_input_fn)
```

The following code sample shows how to load and use the saved model with Python.

```
# Import model from SavedModel
imported = tf.saved_model.load(export_path)

# Use imported model for prediction
def predict(new_object):
  example = tf.train.Example()

  # All regular continuous features
  for column in COLUMN_NAMES[:-2]:
    val = new_object[column]
    example.features.feature[column]. \
      float_list.value.extend([val])

  # One-hot encoded feature of 40 columns
  for val in new_object['Soil_Type']:
    example.features.feature['Soil_Type']. \
      float_list.value.extend([val])

  # Categorical column with ID
  example.features.feature['Cover_Type']. \
    int64_list.value.extend([new_object['Cover_Type']])

  return imported.signatures['predict'](
    examples=tf.constant([example.SerializeToString()]))

predict({
  'Elevation': 2296, 'Aspect': 312, 'Slope': 27,
  'Horizontal_Distance_To_Hydrology': 256,
  'Horizontal_Distance_To_Fire_Points': 836,
  'Horizontal_Distance_To_Roadways': 1273,
  'Vertical_Distance_To_Hydrology': 145,
  'Hillshade_9am': 136, 'Hillshade_Noon': 208,
  'Hillshade_3pm': 206,
  'Soil_Type': [0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
  'Cover_Type': 6})
```

VIP Cheatsheet: Tips and Tricks

Afshine Amidi and Shervine Amidi

November 26, 2018

Data processing

❒ **Data augmentation** – Deep learning models usually need a lot of data to be properly trained. It is often useful to get more data from the existing ones using data augmentation techniques. The main ones are summed up in the table below. More precisely, given the following input image, here are the techniques that we can apply:

Original	Flip	Rotation	Random crop
			
- Image without any modification	- Flipped with respect to an axis for which the meaning of the image is preserved	- Rotation with a slight angle - Simulates incorrect horizon calibration	- Random focus on one part of the image - Several random crops can be done in a row

Color shift	Noise addition	Information loss	Contrast change
			
- Nuances of RGB is slightly changed - Captures noise that can occur with light exposure	- Addition of noise - More tolerance to quality variation of inputs	- Parts of image ignored - Mimics potential loss of parts of image	- Luminosity changes - Controls difference in exposition due to time of day

❒ **Batch normalization** – It is a step of hyperparameter γ, β that normalizes the batch $\{x_i\}$. By noting μ_B, σ_B^2 the mean and variance of that we want to correct to the batch, it is done as follows:

$$\boxed{x_i \longleftarrow \gamma \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}} + \beta}$$

It is usually done after a fully connected/convolutional layer and before a non-linearity layer and aims at allowing higher learning rates and reducing the strong dependence on initialization.

Training a neural network

❒ **Epoch** – In the context of training a model, epoch is a term used to refer to one iteration where the model sees the whole training set to update its weights.

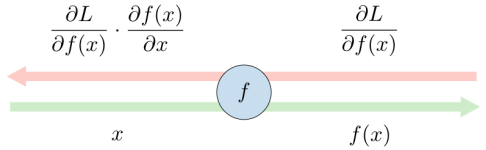
❒ **Mini-batch gradient descent** – During the training phase, updating weights is usually not based on the whole training set at once due to computation complexities or one data point due to noise issues. Instead, the update step is done on mini-batches, where the number of data points in a batch is a hyperparameter that we can tune.

❒ **Loss function** – In order to quantify how a given model performs, the loss function L is usually used to evaluate to what extent the actual outputs y are correctly predicted by the model outputs z.

❒ **Cross-entropy loss** – In the context of binary classification in neural networks, the cross-entropy loss $L(z,y)$ is commonly used and is defined as follows:

$$\boxed{L(z,y) = -\Big[y\log(z) + (1-y)\log(1-z)\Big]}$$

❒ **Backpropagation** – Backpropagation is a method to update the weights in the neural network by taking into account the actual output and the desired output. The derivative with respect to each weight w is computed using the chain rule.

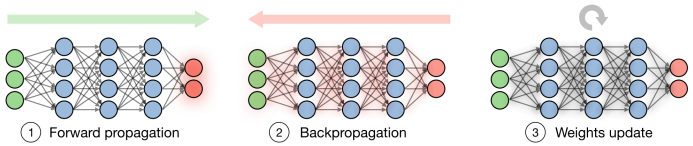


Using this method, each weight is updated with the rule:

$$\boxed{w \longleftarrow w - \alpha \frac{\partial L(z,y)}{\partial w}}$$

❒ **Updating weights** – In a neural network, weights are updated as follows:

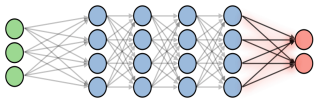
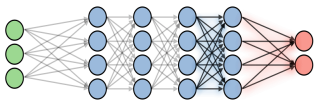
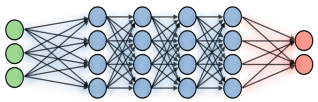
- Step 1: Take a batch of training data and perform forward propagation to compute the loss.
- Step 2: Backpropagate the loss to get the gradient of the loss with respect to each weight.
- Step 3: Use the gradients to update the weights of the network.



Parameter tuning

❒ **Xavier initialization** – Instead of initializing the weights in a purely random manner, Xavier initialization enables to have initial weights that take into account characteristics that are unique to the architecture.

❒ **Transfer learning** – Training a deep learning model requires a lot of data and more importantly a lot of time. It is often useful to take advantage of pre-trained weights on huge datasets that took days/weeks to train, and leverage it towards our use case. Depending on how much data we have at hand, here are the different ways to leverage this:

Training size	Illustration	Explanation
Small		Freezes all layers, trains weights on softmax
Medium		Freezes most layers, trains weights on last layers and softmax
Large		Trains weights on layers and softmax by initializing weights on pre-trained ones

❒ **Learning rate** – The learning rate, often noted α or sometimes η, indicates at which pace the weights get updated. It can be fixed or adaptively changed. The current most popular method is called Adam, which is a method that adapts the learning rate.

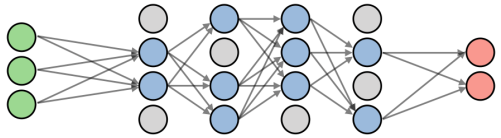
❒ **Adaptive learning rates** – Letting the learning rate vary when training a model can reduce the training time and improve the numerical optimal solution. While Adam optimizer is the most commonly used technique, others can also be useful. They are summed up in the table below:

Method	Explanation	Update of w	Update of b
Momentum	- Dampens oscillations - Improvement to SGD - 2 parameters to tune	$w - \alpha v_{dw}$	$b - \alpha v_{db}$
RMSprop	- Root Mean Square propagation - Speeds up learning algorithm by controlling oscillations	$w - \alpha \frac{dw}{\sqrt{s_{dw}}}$	$b \longleftarrow b - \alpha \frac{db}{\sqrt{s_{db}}}$
Adam	- Adaptive Moment estimation - Most popular method - 4 parameters to tune	$w - \alpha \frac{v_{dw}}{\sqrt{s_{dw}} + \epsilon}$	$b \longleftarrow b - \alpha \frac{v_{db}}{\sqrt{s_{db}} + \epsilon}$

Remark: other methods include Adadelta, Adagrad and SGD.

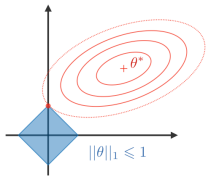
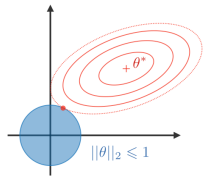
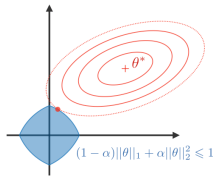
Regularization

❒ **Dropout** – Dropout is a technique used in neural networks to prevent overfitting the training data by dropping out neurons with probability $p > 0$. It forces the model to avoid relying too much on particular sets of features.

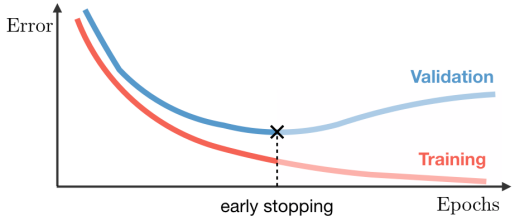


Remark: most deep learning frameworks parametrize dropout through the 'keep' parameter $1-p$.

❒ **Weight regularization** – In order to make sure that the weights are not too large and that the model is not overfitting the training set, regularization techniques are usually performed on the model weights. The main ones are summed up in the table below:

LASSO	Ridge	Elastic Net
- Shrinks coefficients to 0 - Good for variable selection	Makes coefficients smaller	Tradeoff between variable selection and small coefficients
		
$\ldots + \lambda \|\|\theta\|\|_1$ $\lambda \in \mathbb{R}$	$\ldots + \lambda \|\|\theta\|\|_2^2$ $\lambda \in \mathbb{R}$	$\ldots + \lambda \left[(1-\alpha) \|\|\theta\|\|_1 + \alpha \|\|\theta\|\|_2^2 \right]$ $\lambda \in \mathbb{R}, \alpha \in [0,1]$

❒ **Early stopping** – This regularization technique stops the training process as soon as the validation loss reaches a plateau or starts to increase.



Good practices

❒ **Overfitting small batch** – When debugging a model, it is often useful to make quick tests to see if there is any major issue with the architecture of the model itself. In particular, in order to make sure that the model can be properly trained, a mini-batch is passed inside the network to see if it can overfit on it. If it cannot, it means that the model is either too complex or not complex enough to even overfit on a small batch, let alone a normal-sized training set.

❒ **Gradient checking** – Gradient checking is a method used during the implementation of the backward pass of a neural network. It compares the value of the analytical gradient to the numerical gradient at given points and plays the role of a sanity-check for correctness.

	Numerical gradient	**Analytical gradient**
Formula	$\frac{df}{dx}(x) \approx \frac{f(x+h)-f(x-h)}{2h}$	$\frac{df}{dx}(x) = f'(x)$
Comments	- Expensive; loss has to be computed two times per dimension - Used to verify correctness of analytical implementation -Trade-off in choosing h not too small (numerical instability) nor too large (poor gradient approx.)	- 'Exact' result - Direct computation - Used in the final implementation

⋆ ⋆ ⋆

VIP Cheatsheet: Deep Learning

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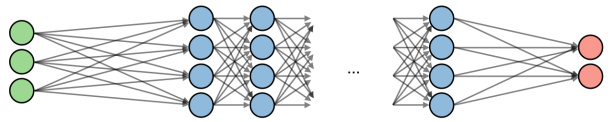
September 15, 2018

Neural Networks

Neural networks are a class of models that are built with layers. Commonly used types of neural networks include convolutional and recurrent neural networks.

❒ **Architecture** – The vocabulary around neural networks architectures is described in the figure below:

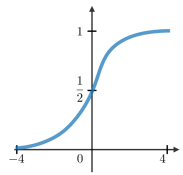
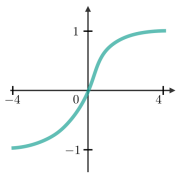
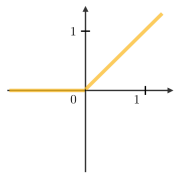
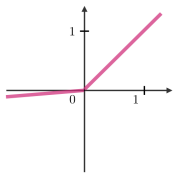


By noting i the i^{th} layer of the network and j the j^{th} hidden unit of the layer, we have:

$$\boxed{z_j^{[i]} = {w_j^{[i]}}^T x + b_j^{[i]}}$$

where we note w, b, z the weight, bias and output respectively.

❒ **Activation function** – Activation functions are used at the end of a hidden unit to introduce non-linear complexities to the model. Here are the most common ones:

Sigmoid	Tanh	ReLU	Leaky ReLU
$g(z) = \frac{1}{1+e^{-z}}$	$g(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$	$g(z) = \max(0,z)$	$g(z) = \max(\epsilon z, z)$ with $\epsilon \ll 1$
			

❒ **Cross-entropy loss** – In the context of neural networks, the cross-entropy loss $L(z,y)$ is commonly used and is defined as follows:

$$\boxed{L(z,y) = -\Big[y\log(z) + (1-y)\log(1-z)\Big]}$$

❒ **Learning rate** – The learning rate, often noted η, indicates at which pace the weights get updated. This can be fixed or adaptively changed. The current most popular method is called Adam, which is a method that adapts the learning rate.

❒ **Backpropagation** – Backpropagation is a method to update the weights in the neural network by taking into account the actual output and the desired output. The derivative with respect to weight w is computed using chain rule and is of the following form:

$$\boxed{\frac{\partial L(z,y)}{\partial w} = \frac{\partial L(z,y)}{\partial a} \times \frac{\partial a}{\partial z} \times \frac{\partial z}{\partial w}}$$

As a result, the weight is updated as follows:

$$\boxed{w \longleftarrow w - \eta \frac{\partial L(z,y)}{\partial w}}$$

❒ **Updating weights** – In a neural network, weights are updated as follows:

- Step 1: Take a batch of training data.
- Step 2: Perform forward propagation to obtain the corresponding loss.
- Step 3: Backpropagate the loss to get the gradients.
- Step 4: Use the gradients to update the weights of the network.

❒ **Dropout** – Dropout is a technique meant at preventing overfitting the training data by dropping out units in a neural network. In practice, neurons are either dropped with probability p or kept with probability $1-p$.

Convolutional Neural Networks

❒ **Convolutional layer requirement** – By noting W the input volume size, F the size of the convolutional layer neurons, P the amount of zero padding, then the number of neurons N that fit in a given volume is such that:

$$\boxed{N = \frac{W - F + 2P}{S} + 1}$$

❒ **Batch normalization** – It is a step of hyperparameter γ, β that normalizes the batch $\{x_i\}$. By noting μ_B, σ_B^2 the mean and variance of that we want to correct to the batch, it is done as follows:

$$\boxed{x_i \longleftarrow \gamma \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}} + \beta}$$

It is usually done after a fully connected/convolutional layer and before a non-linearity layer and aims at allowing higher learning rates and reducing the strong dependence on initialization.

Recurrent Neural Networks

❒ **Types of gates** – Here are the different types of gates that we encounter in a typical recurrent neural network:

Input gate	Forget gate	Output gate	Gate
Write to cell or not?	Erase a cell or not?	Reveal a cell or not?	How much writing?

❒ **LSTM** – A long short-term memory (LSTM) network is a type of RNN model that avoids the vanishing gradient problem by adding 'forget' gates.

Reinforcement Learning and Control

The goal of reinforcement learning is for an agent to learn how to evolve in an environment.

❒ **Markov decision processes** – A Markov decision process (MDP) is a 5-tuple $(S,A,\{P_{sa}\},\gamma,R)$ where:

- $\mathcal{S}$ is the set of states
- $\mathcal{A}$ is the set of actions
- $\{P_{sa}\}$ are the state transition probabilities for $s \in \mathcal{S}$ and $a \in \mathcal{A}$
- $\gamma \in [0,1[$ is the discount factor
- $R : \mathcal{S} \times \mathcal{A} \longrightarrow \mathbb{R}$ or $R : \mathcal{S} \longrightarrow \mathbb{R}$ is the reward function that the algorithm wants to maximize

❒ **Policy** – A policy π is a function $\pi : \mathcal{S} \longrightarrow \mathcal{A}$ that maps states to actions.

Remark: we say that we execute a given policy π if given a state s we take the action $a = \pi(s)$.

❒ **Value function** – For a given policy π and a given state s, we define the value function V^π as follows:

$$\boxed{V^\pi(s) = E\Big[R(s_0) + \gamma R(s_1) + \gamma^2 R(s_2) + ...|s_0 = s,\pi\Big]}$$

❒ **Bellman equation** – The optimal Bellman equations characterizes the value function V^{π^*} of the optimal policy π^*:

$$\boxed{V^{\pi^*}(s) = R(s) + \max_{a\in\mathcal{A}} \gamma \sum_{s'\in S} P_{sa}(s')V^{\pi^*}(s')}$$

Remark: we note that the optimal policy π^* for a given state s is such that:

$$\boxed{\pi^*(s) = \underset{a\in\mathcal{A}}{\text{argmax}} \sum_{s'\in\mathcal{S}} P_{sa}(s')V^*(s')}$$

❒ **Value iteration algorithm** – The value iteration algorithm is in two steps:

- We initialize the value:

$$\boxed{V_0(s) = 0}$$

- We iterate the value based on the values before:

$$\boxed{V_{i+1}(s) = R(s) + \max_{a\in\mathcal{A}} \left[\sum_{s'\in\mathcal{S}} \gamma P_{sa}(s')V_i(s')\right]}$$

❒ **Maximum likelihood estimate** – The maximum likelihood estimates for the state transition probabilities are as follows:

$$\boxed{P_{sa}(s') = \frac{\#\text{times took action } a \text{ in state } s \text{ and got to } s'}{\#\text{times took action } a \text{ in state } s}}$$

❒ **Q-learning** – Q-learning is a model-free estimation of Q, which is done as follows:

$$\boxed{Q(s,a) \leftarrow Q(s,a) + \alpha\Big[R(s,a,s') + \gamma \max_{a'} Q(s',a') - Q(s,a)\Big]}$$

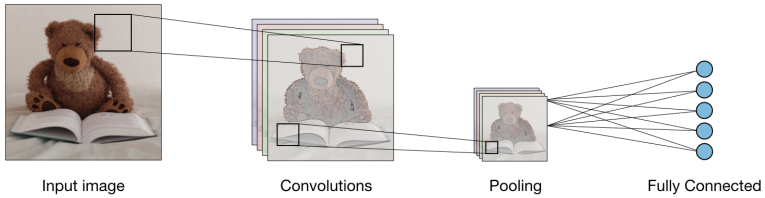
VIP Cheatsheet: Convolutional Neural Networks

Afshine Amidi and Shervine Amidi

November 26, 2018

Overview

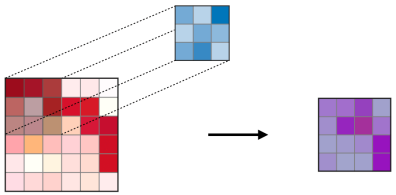
❒ **Architecture of a traditional CNN** – Convolutional neural networks, also known as CNNs, are a specific type of neural networks that are generally composed of the following layers:



The convolution layer and the pooling layer can be fine-tuned with respect to hyperparameters that are described in the next sections.

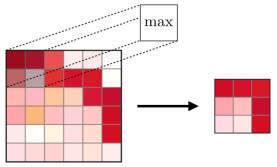
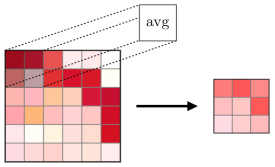
Types of layer

❒ **Convolutional layer (CONV)** – The convolution layer (CONV) uses filters that perform convolution operations as it is scanning the input I with respect to its dimensions. Its hyperparameters include the filter size F and stride S. The resulting output O is called *feature map* or *activation map*.

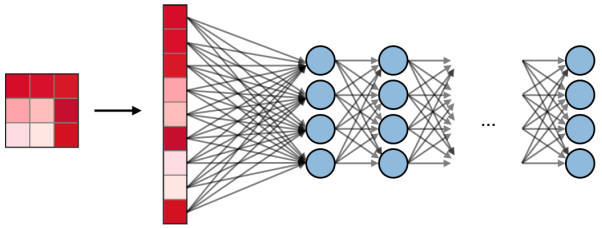


Remark: the convolution step can be generalized to the 1D and 3D cases as well.

❒ **Pooling (POOL)** – The pooling layer (POOL) is a downsampling operation, typically applied after a convolution layer, which does some spatial invariance. In particular, max and average pooling are special kinds of pooling where the maximum and average value is taken, respectively.

	Max pooling	Average pooling
Purpose	Each pooling operation selects the maximum value of the current view	Each pooling operation averages the values of the current view
Illustration		
Comments	- Preserves detected features - Most commonly used	- Downsamples feature map - Used in LeNet

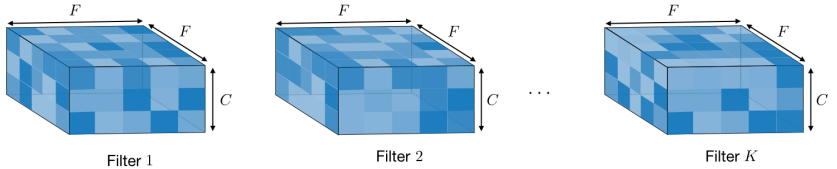
❒ **Fully Connected (FC)** – The fully connected layer (FC) operates on a flattened input where each input is connected to all neurons. If present, FC layers are usually found towards the end of CNN architectures and can be used to optimize objectives such as class scores.



Filter hyperparameters

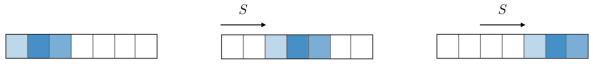
The convolution layer contains filters for which it is important to know the meaning behind its hyperparameters.

❒ **Dimensions of a filter** – A filter of size $F \times F$ applied to an input containing C channels is a $F \times F \times C$ volume that performs convolutions on an input of size $I \times I \times C$ and produces an output feature map (also called activation map) of size $O \times O \times 1$.

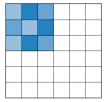
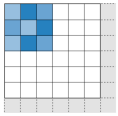
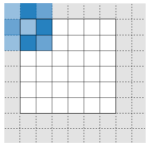


Remark: the application of K filters of size $F \times F$ results in an output feature map of size $O \times O \times K$.

❒ **Stride** – For a convolutional or a pooling operation, the stride S denotes the number of pixels by which the window moves after each operation.



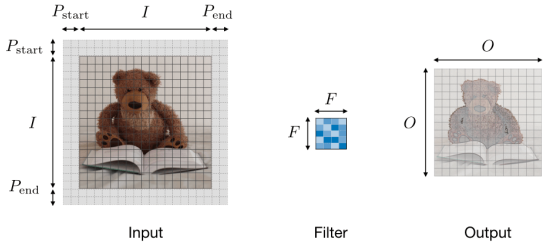
❒ **Zero-padding** – Zero-padding denotes the process of adding P zeroes to each side of the boundaries of the input. This value can either be manually specified or automatically set through one of the three modes detailed below:

	Valid	Same	Full
Value	$P = 0$	$P_{\text{start}} = \left\lfloor \frac{S\lceil \frac{I}{S} \rceil - I + F - S}{2} \right\rfloor$ $P_{\text{end}} = \left\lceil \frac{S\lceil \frac{I}{S} \rceil - I + F - S}{2} \right\rceil$	$P_{\text{start}} \in [\![0, F-1]\!]$ $P_{\text{end}} = F - 1$
Illustration			
Purpose	- No padding - Drops last convolution if dimensions do not match	- Padding such that feature map size has size $\left\lceil \frac{I}{S} \right\rceil$ - Output size is mathematically convenient - Also called 'half' padding	- Maximum padding such that end convolutions are applied on the limits of the input - Filter 'sees' the input end-to-end

Tuning hyperparameters

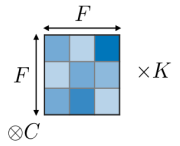
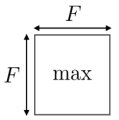
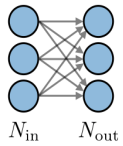
❒ **Parameter compatibility in convolution layer** – By noting I the length of the input volume size, F the length of the filter, P the amount of zero padding, S the stride, then the output size O of the feature map along that dimension is given by:

$$\boxed{O = \frac{I - F + P_{\text{start}} + P_{\text{end}}}{S} + 1}$$



Remark: often times, $P_{start} = P_{end} \triangleq P$, in which case we can replace $P_{start} + P_{end}$ by $2P$ in the formula above.

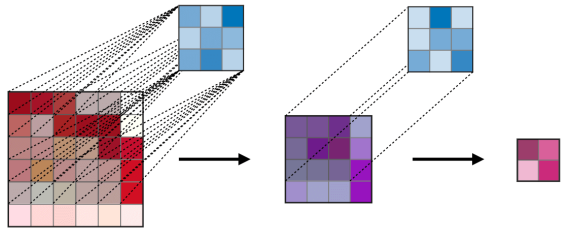
❒ **Understanding the complexity of the model** – In order to assess the complexity of a model, it is often useful to determine the number of parameters that its architecture will have. In a given layer of a convolutional neural network, it is done as follows:

	CONV	POOL	FC
Illustration			
Input size	$I \times I \times C$	$I \times I \times C$	N_{in}
Output size	$O \times O \times K$	$O \times O \times C$	N_{out}
Number of parameters	$(F \times F \times C + 1) \cdot K$	0	$(N_{\text{in}} + 1) \times N_{\text{out}}$
Remarks	- One bias parameter per filter - In most cases, $S < F$ - A common choice for K is $2C$	- Pooling operation done channel-wise - In most cases, $S = F$	- Input is flattened - One bias parameter per neuron - The number of FC neurons is free of structural constraints

❒ **Receptive field** – The receptive field at layer k is the area denoted $R_k \times R_k$ of the input that each pixel of the k-th activation map can 'see'. By calling F_j the filter size of layer j and S_i the stride value of layer i and with the convention $S_0 = 1$, the receptive field at layer k can be computed with the formula:

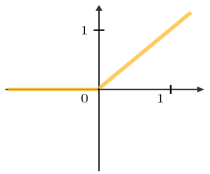
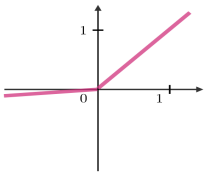
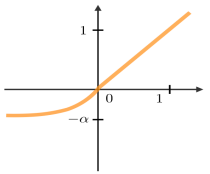
$$\boxed{R_k = 1 + \sum_{j=1}^{k} (F_j - 1) \prod_{i=0}^{j-1} S_i}$$

In the example below, we have $F_1 = F_2 = 3$ and $S_1 = S_2 = 1$, which gives $R_2 = 1+2 \cdot 1+2 \cdot 1 = 5$.



Commonly used activation functions

❒ **Rectified Linear Unit** – The rectified linear unit layer (ReLU) is an activation function g that is used on all elements of the volume. It aims at introducing non-linearities to the network. Its variants are summarized in the table below:

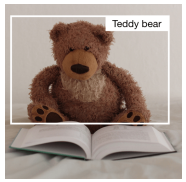
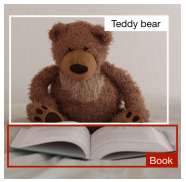
ReLU	Leaky ReLU	ELU
$g(z) = \max(0,z)$	$g(z) = \max(\epsilon z, z)$ with $\epsilon \ll 1$	$g(z) = \max(\alpha(e^z - 1), z)$ with $\alpha \ll 1$
		
Non-linearity complexities biologically interpretable	Addresses dying ReLU issue for negative values	Differentiable everywhere

❒ **Softmax** – The softmax step can be seen as a generalized logistic function that takes as input a vector of scores $x \in \mathbb{R}^n$ and outputs a vector of output probability $p \in \mathbb{R}^n$ through a softmax function at the end of the architecture. It is defined as follows:

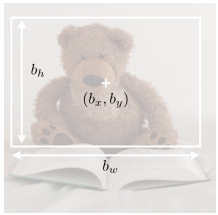
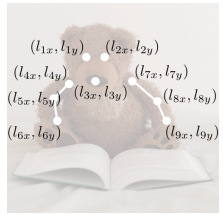
$$p = \begin{pmatrix} p_1 \\ \vdots \\ p_n \end{pmatrix} \quad \text{where} \quad p_i = \frac{e^{x_i}}{\sum_{j=1}^{n} e^{x_j}}$$

Object detection

❒ **Types of models** – There are 3 main types of object recognition algorithms, for which the nature of what is predicted is different. They are described in the table below:

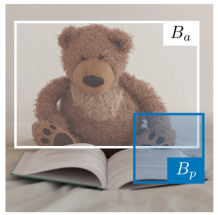
Image classification	Classification w. localization	Detection
		
- Classifies a picture - Predicts probability of object	- Detects object in a picture - Predicts probability of object and where it is located	- Detects up to several objects in a picture - Predicts probabilities of objects and where they are located
Traditional CNN	Simplified YOLO, R-CNN	YOLO, R-CNN

❒ **Detection** – In the context of object detection, different methods are used depending on whether we just want to locate the object or detect a more complex shape in the image. The two main ones are summed up in the table below:

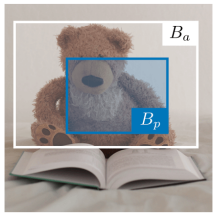
Bounding box detection	Landmark detection
Detects the part of the image where the object is located	- Detects a shape or characteristics of an object (e.g. eyes) - More granular
	
Box of center (b_x,b_y), height b_h and width b_w	Reference points (l_{1x},l_{1y}), ...,(l_{nx},l_{ny})

❒ **Intersection over Union** – Intersection over Union, also known as IoU, is a function that quantifies how correctly positioned a predicted bounding box B_p is over the actual bounding box B_a. It is defined as:

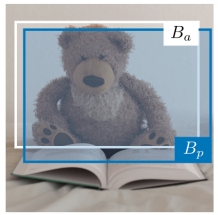
$$\text{IoU}(B_p,B_a) = \frac{B_p \cap B_a}{B_p \cup B_a}$$



$\text{IoU}(B_p, B_a) = 0.1$



$\text{IoU}(B_p, B_a) = 0.5$



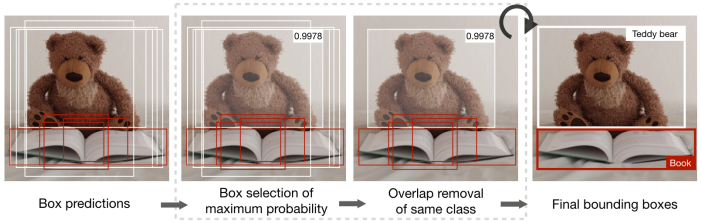
$\text{IoU}(B_p, B_a) = 0.9$

Remark: we always have $IoU \in [0,1]$. By convention, a predicted bounding box B_p is considered as being reasonably good if $IoU(B_p,B_a) \geqslant 0.5$.

❒ **Anchor boxes** – Anchor boxing is a technique used to predict overlapping bounding boxes. In practice, the network is allowed to predict more than one box simultaneously, where each box prediction is constrained to have a given set of geometrical properties. For instance, the first prediction can potentially be a rectangular box of a given form, while the second will be another rectangular box of a different geometrical form.

❒ **Non-max suppression** – The non-max suppression technique aims at removing duplicate overlapping bounding boxes of a same object by selecting the most representative ones. After having removed all boxes having a probability prediction lower than 0.6, the following steps are repeated while there are boxes remaining:

- Step 1: Pick the box with the largest prediction probability.
- Step 2: Discard any box having an IoU $\geqslant 0.5$ with the previous box.



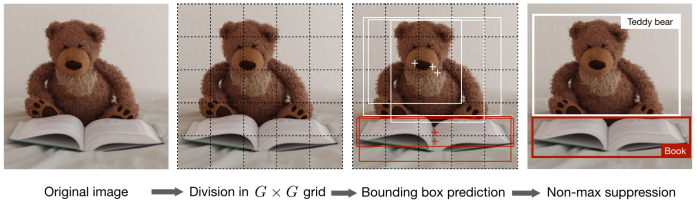
❒ **YOLO** – You Only Look Once (YOLO) is an object detection algorithm that performs the following steps:

- Step 1: Divide the input image into a $G \times G$ grid.
- Step 2: For each grid cell, run a CNN that predicts y of the following form:

$$y = \Big[\underbrace{p_c, b_x, b_y, b_h, b_w, c_1, c_2, ..., c_p}_{\text{repeated } k \text{ times}}, ...\Big]^T \in \mathbb{R}^{G \times G \times k \times (5+p)}$$

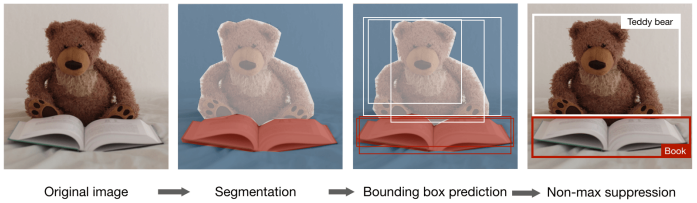
where p_c is the probability of detecting an object, b_x, b_y, b_h, b_w are the properties of the detected bouding box, $c_1, ..., c_p$ is a one-hot representation of which of the p classes were detected, and k is the number of anchor boxes.

- Step 3: Run the non-max suppression algorithm to remove any potential duplicate overlapping bounding boxes.



Remark: when $p_c = 0$, then the network does not detect any object. In that case, the corresponding predictions $b_x, ..., c_p$ have to be ignored.

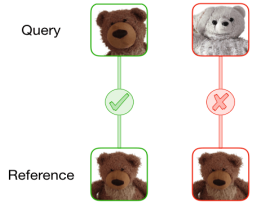
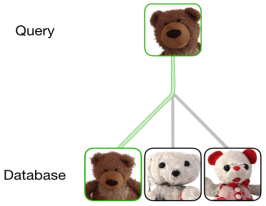
❒ **R-CNN** – Region with Convolutional Neural Networks (R-CNN) is an object detection algorithm that first segments the image to find potential relevant bounding boxes and then run the detection algorithm to find most probable objects in those bounding boxes.



Remark: although the original algorithm is computationally expensive and slow, newer architectures enabled the algorithm to run faster, such as Fast R-CNN and Faster R-CNN.

Face verification and recognition

❒ **Types of models** – Two main types of model are summed up in table below:

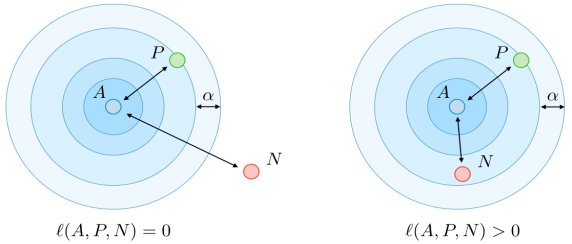
Face verification	Face recognition
- Is this the correct person? - One-to-one lookup	- Is this one of the K persons in the database? - One-to-many lookup
	

❒ **One Shot Learning** – One Shot Learning is a face verification algorithm that uses a limited training set to learn a similarity function that quantifies how different two given images are. The similarity function applied to two images is often noted $d(\text{image 1}, \text{image 2})$.

❒ **Siamese Network** – Siamese Networks aim at learning how to encode images to then quantify how different two images are. For a given input image $x^{(i)}$, the encoded output is often noted as $f(x^{(i)})$.

❒ **Triplet loss** – The triplet loss ℓ is a loss function computed on the embedding representation of a triplet of images A (anchor), P (positive) and N (negative). The anchor and the positive example belong to a same class, while the negative example to another one. By calling $\alpha \in \mathbb{R}^+$ the margin parameter, this loss is defined as follows:

$$\ell(A,P,N) = \max\left(d(A,P) - d(A,N) + \alpha, 0\right)$$



Neural style transfer

❒ **Motivation** – The goal of neural style transfer is to generate an image G based on a given content C and a given style S.

❒ **Activation** – In a given layer l, the activation is noted $a^{[l]}$ and is of dimensions $n_H \times n_w \times n_c$

❒ **Content cost function** – The content cost function $J_{\text{content}}(C,G)$ is used to determine how the generated image G differs from the original content image C. It is defined as follows:

$$\boxed{J_{\text{content}}(C,G) = \frac{1}{2}||a^{[l](C)} - a^{[l](G)}||^2}$$

❒ **Style matrix** – The style matrix $G^{[l]}$ of a given layer l is a Gram matrix where each of its elements $G^{[l]}_{kk'}$ quantifies how correlated the channels k and k' are. It is defined with respect to activations $a^{[l]}$ as follows:

$$\boxed{G^{[l]}_{kk'} = \sum_{i=1}^{n_H^{[l]}} \sum_{j=1}^{n_w^{[l]}} a^{[l]}_{ijk} a^{[l]}_{ijk'}}$$

Remark: the style matrix for the style image and the generated image are noted $G^{[l](S)}$ and $G^{[l](G)}$ respectively.

❒ **Style cost function** – The style cost function $J_{\text{style}}(S,G)$ is used to determine how the generated image G differs from the style S. It is defined as follows:

$$\boxed{J^{[l]}_{\text{style}}(S,G) = \frac{1}{(2n_H n_w n_c)^2}||G^{[l](S)} - G^{[l](G)}||^2_F = \frac{1}{(2n_H n_w n_c)^2} \sum_{k,k'=1}^{n_c} \left(G^{[l](S)}_{kk'} - G^{[l](G)}_{kk'}\right)^2}$$

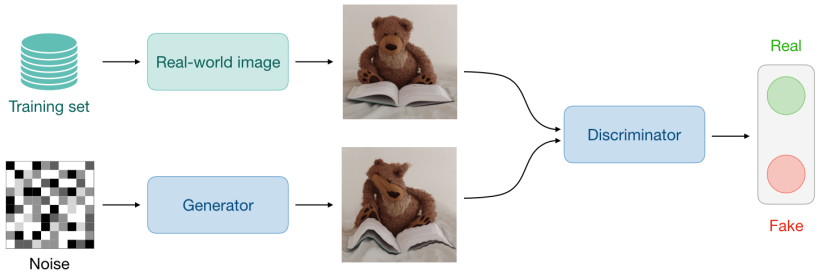
❒ **Overall cost function** – The overall cost function is defined as being a combination of the content and style cost functions, weighted by parameters α,β, as follows:

$$\boxed{J(G) = \alpha J_{\text{content}}(C,G) + \beta J_{\text{style}}(S,G)}$$

Remark: a higher value of α will make the model care more about the content while a higher value of β will make it care more about the style.

Architectures using computational tricks

❒ **Generative Adversarial Network** – Generative adversarial networks, also known as GANs, are composed of a generative and a discriminative model, where the generative model aims at generating the most truthful output that will be fed into the discriminative which aims at differentiating the generated and true image.



Remark: use cases using variants of GANs include text to image, music generation and synthesis.

❒ **ResNet** – The Residual Network architecture (also called ResNet) uses residual blocks with a high number of layers meant to decrease the training error. The residual block has the following characterizing equation:

$$\boxed{a^{[l+2]} = g(a^{[l]} + z^{[l+2]})}$$

❒ **Inception Network** – This architecture uses inception modules and aims at giving a try at different convolutions in order to increase its performance. In particular, it uses the 1×1 convolution trick to lower the burden of computation.

⋆ ⋆ ⋆

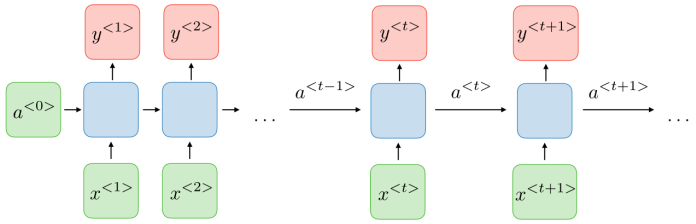
VIP Cheatsheet: Recurrent Neural Networks

Afshine Amidi and Shervine Amidi

November 26, 2018

Overview

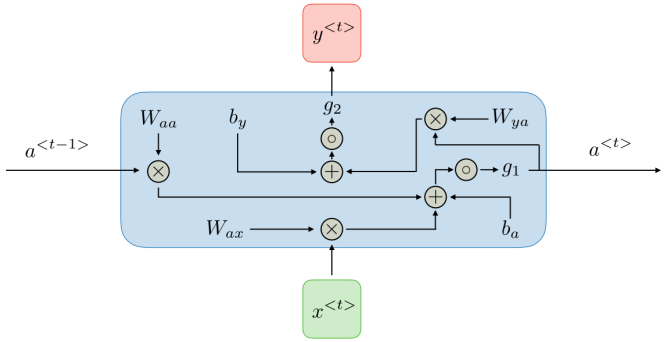
❒ **Architecture of a traditional RNN** – Recurrent neural networks, also known as RNNs, are a class of neural networks that allow previous outputs to be used as inputs while having hidden states. They are typically as follows:



For each timestep t, the activation $a^{<t>}$ and the output $y^{<t>}$ are expressed as follows:

$$\boxed{a^{<t>} = g_1(W_{aa}a^{<t-1>} + W_{ax}x^{<t>} + b_a)} \quad \text{and} \quad \boxed{y^{<t>} = g_2(W_{ya}a^{<t>} + b_y)}$$

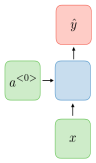
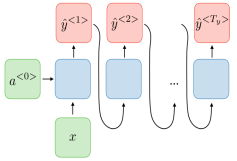
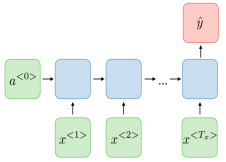
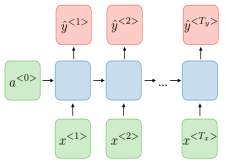
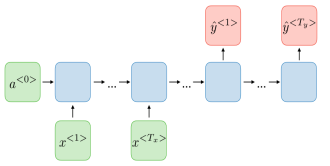
where $W_{ax}, W_{aa}, W_{ya}, b_a, b_y$ are coefficients that are shared temporally and g_1, g_2 activation functions



The pros and cons of a typical RNN architecture are summed up in the table below:

Advantages	Drawbacks
- Possibility of processing input of any length - Model size not increasing with size of input - Computation takes into account historical information - Weights are shared across time	- Computation being slow - Difficulty of accessing information from a long time ago - Cannot consider any future input for the current state

❒ **Applications of RNNs** – RNN models are mostly used in the fields of natural language processing and speech recognition. The different applications are summed up in the table below:

Type of RNN	Illustration	Example
One-to-one $T_x = T_y = 1$		Traditional neural network
One-to-many $T_x = 1, T_y > 1$		Music generation
Many-to-one $T_x > 1, T_y = 1$		Sentiment classification
Many-to-many $T_x = T_y$		Name entity recognition
Many-to-many $T_x \neq T_y$		Machine translation

❒ **Loss function** – In the case of a recurrent neural network, the loss function $\mathcal{L}$ of all time

steps is defined based on the loss at every time step as follows:

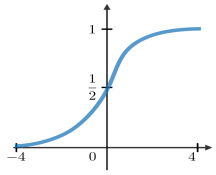
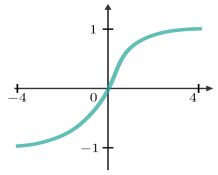
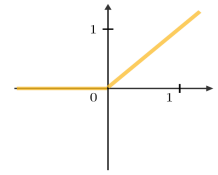
$$\mathcal{L}(\widehat{y},y)=\sum_{t=1}^{T_y}\mathcal{L}(\widehat{y}^{<t>},y^{<t>})$$

❒ **Backpropagation through time** – Backpropagation is done at each point in time. At timestep T, the derivative of the loss $\mathcal{L}$ with respect to weight matrix W is expressed as follows:

$$\frac{\partial\mathcal{L}^{(T)}}{\partial W}=\sum_{t=1}^{T}\left.\frac{\partial\mathcal{L}^{(T)}}{\partial W}\right|_{(t)}$$

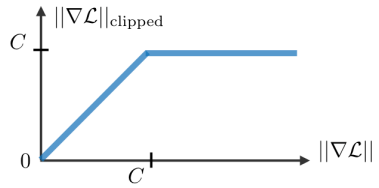
Handling long term dependencies

❒ **Commonly used activation functions** – The most common activation functions used in RNN modules are described below:

Sigmoid	Tanh	RELU
$g(z)=\frac{1}{1+e^{-z}}$	$g(z)=\frac{e^z-e^{-z}}{e^z+e^{-z}}$	$g(z)=\max(0,z)$
		

❒ **Vanishing/exploding gradient** – The vanishing and exploding gradient phenomena are often encountered in the context of RNNs. The reason why they happen is that it is difficult to capture long term dependencies because of multiplicative gradient that can be exponentially decreasing/increasing with respect to the number of layers.

❒ **Gradient clipping** – It is a technique used to cope with the exploding gradient problem sometimes encountered when performing backpropagation. By capping the maximum value for the gradient, this phenomenon is controlled in practice.



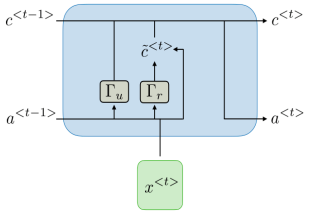
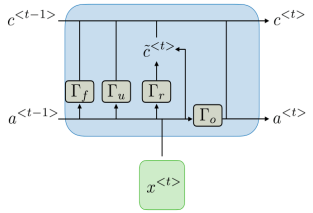
❒ **Types of gates** – In order to remedy the vanishing gradient problem, specific gates are used in some types of RNNs and usually have a well-defined purpose. They are usually noted Γ and are equal to:

$$\Gamma=\sigma(Wx^{<t>}+Ua^{<t-1>}+b)$$

where W,U,b are coefficients specific to the gate and σ is the sigmoid function. The main ones are summed up in the table below:

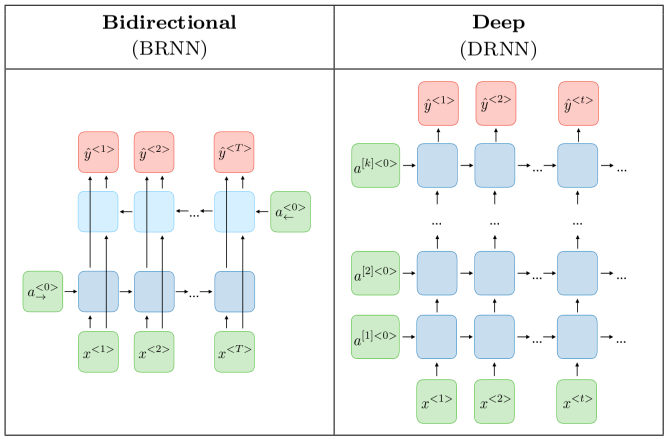
Type of gate	Role	Used in
Update gate Γ_u	How much past should matter now?	GRU, LSTM
Relevance gate Γ_r	Drop previous information?	GRU, LSTM
Forget gate Γ_f	Erase a cell or not?	LSTM
Output gate Γ_o	How much to reveal of a cell?	LSTM

❒ **GRU/LSTM** – Gated Recurrent Unit (GRU) and Long Short-Term Memory units (LSTM) deal with the vanishing gradient problem encountered by traditional RNNs, with LSTM being a generalization of GRU. Below is a table summing up the characterizing equations of each architecture:

	Gated Recurrent Unit (GRU)	Long Short-Term Memory (LSTM)
$\tilde{c}^{<t>}$	$\tanh(W_c[\Gamma_r\star a^{<t-1>},x^{<t>}]+b_c)$	$\tanh(W_c[\Gamma_r\star a^{<t-1>},x^{<t>}]+b_c)$
$c^{<t>}$	$\Gamma_u\star\tilde{c}^{<t>}+(1-\Gamma_u)\star c^{<t-1>}$	$\Gamma_u\star\tilde{c}^{<t>}+\Gamma_f\star c^{<t-1>}$
$a^{<t>}$	$c^{<t>}$	$\Gamma_o\star c^{<t>}$
Dependencies		

Remark: the sign $\star$ denotes the element-wise multiplication between two vectors.

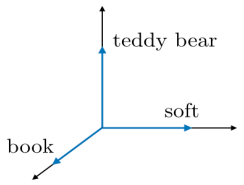
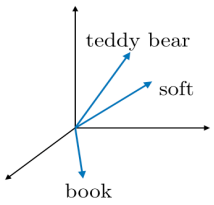
❒ **Variants of RNNs** – The table below sums up the other commonly used RNN architectures:



Learning word representation

In this section, we note V the vocabulary and $|V|$ its size.

❒ **Representation techniques** – The two main ways of representing words are summed up in the table below:

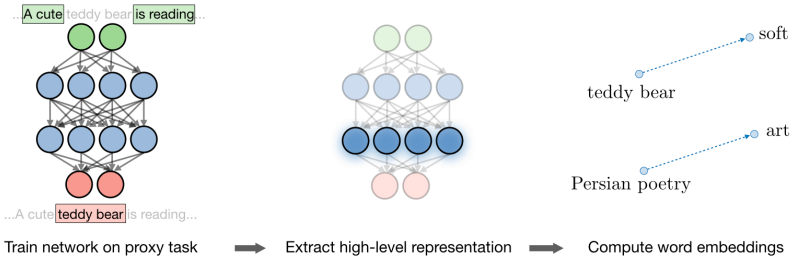
1-hot representation	Word embedding
	
- Noted o_w - Naive approach, no similarity information	- Noted e_w - Takes into account words similarity

❒ **Embedding matrix** – For a given word w, the embedding matrix E is a matrix that maps its 1-hot representation o_w to its embedding e_w as follows:

$$\boxed{e_w = Eo_w}$$

Remark: learning the embedding matrix can be done using target/context likelihood models.

❒ **Word2vec** – Word2vec is a framework aimed at learning word embeddings by estimating the likelihood that a given word is surrounded by other words. Popular models include skip-gram, negative sampling and CBOW.



❒ **Skip-gram** – The skip-gram word2vec model is a supervised learning task that learns word embeddings by assessing the likelihood of any given target word t happening with a context word c. By noting θ_t a parameter associated with t, the probability $P(t|c)$ is given by:

$$\boxed{P(t|c) = \frac{\exp(\theta_t^T e_c)}{\sum_{j=1}^{|V|} \exp(\theta_j^T e_c)}}$$

Remark: summing over the whole vocabulary in the denominator of the softmax part makes this model computationally expensive. CBOW is another word2vec model using the surrounding words to predict a given word.

❒ **Negative sampling** – It is a set of binary classifiers using logistic regressions that aim at assessing how a given context and a given target words are likely to appear simultaneously, with the models being trained on sets of k negative examples and 1 positive example. Given a context word c and a target word t, the prediction is expressed by:

$$\boxed{P(y = 1|c,t) = \sigma(\theta_t^T e_c)}$$

Remark: this method is less computationally expensive than the skip-gram model.

❒ **GloVe** – The GloVe model, short for global vectors for word representation, is a word embedding technique that uses a co-occurence matrix X where each $X_{i,j}$ denotes the number of times that a target i occurred with a context j. Its cost function J is as follows:

$$\boxed{J(\theta) = \frac{1}{2}\sum_{i,j=1}^{|V|} f(X_{ij})(\theta_i^T e_j + b_i + b'_j - \log(X_{ij}))^2}$$

here f is a weighting function such that $X_{i,j} = 0 \Longrightarrow f(X_{i,j}) = 0$.

Given the symmetry that e and θ play in this model, the final word embedding $e_w^{(\text{final})}$ is given by:

$$\boxed{e_w^{(\text{final})} = \frac{e_w + \theta_w}{2}}$$

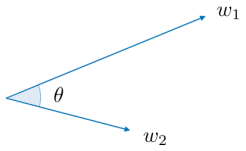
Remark: the individual components of the learned word embeddings are not necessarily interpretable.

Comparing words

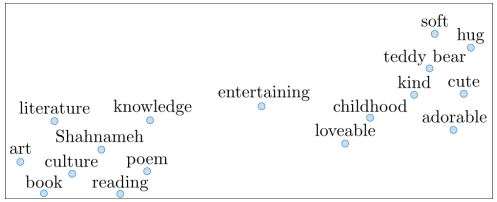
❒ **Cosine similarity** – The cosine similarity between words w_1 and w_2 is expressed as follows:

$$\text{similarity} = \frac{w_1 \cdot w_2}{||w_1||\,||w_2||} = \cos(\theta)$$

Remark: θ is the angle between words w_1 and w_2.



❒ **t-SNE** – t-SNE (t-distributed Stochastic Neighbor Embedding) is a technique aimed at reducing high-dimensional embeddings into a lower dimensional space. In practice, it is commonly used to visualize word vectors in the 2D space.



Language model

❒ **Overview** – A language model aims at estimating the probability of a sentence $P(y)$.

❒ **n-gram model** – This model is a naive approach aiming at quantifying the probability that an expression appears in a corpus by counting its number of appearance in the training data.

❒ **Perplexity** – Language models are commonly assessed using the perplexity metric, also known as PP, which can be interpreted as the inverse probability of the dataset normalized by the number of words T. The perplexity is such that the lower, the better and is defined as follows:

$$\text{PP} = \prod_{t=1}^{T}\left(\frac{1}{\sum_{j=1}^{|V|} y_j^{(t)} \cdot \widehat{y}_j^{(t)}}\right)^{\frac{1}{T}}$$

Remark: PP is commonly used in t-SNE.

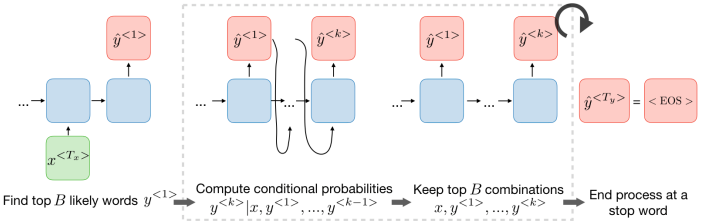
Machine translation

❒ **Overview** – A machine translation model is similar to a language model except it has an encoder network placed before. For this reason, it is sometimes referred as a conditional language model. The goal is to find a sentence y such that:

$$y = \underset{y^{<1>},\ldots,y^{<T_y>}}{\arg\max}\; P(y^{<1>},\ldots,y^{<T_y>}|x)$$

❒ **Beam search** – It is a heuristic search algorithm used in machine translation and speech recognition to find the likeliest sentence y given an input x.

- Step 1: Find top B likely words $y^{<1>}$
- Step 2: Compute conditional probabilities $y^{<k>}|x,y^{<1>},\ldots,y^{<k-1>}$
- Step 3: Keep top B combinations $x,y^{<1>},\ldots,y^{<k>}$



Remark: if the beam width is set to 1, then this is equivalent to a naive greedy search.

❒ **Beam width** – The beam width B is a parameter for beam search. Large values of B yield to better result but with slower performance and increased memory. Small values of B lead to worse results but is less computationally intensive. A standard value for B is around 10.

❒ **Length normalization** – In order to improve numerical stability, beam search is usually applied on the following normalized objective, often called the normalized log-likelihood objective, defined as:

$$\text{Objective} = \frac{1}{T_y^{\alpha}}\sum_{t=1}^{T_y}\log\left[p(y^{<t>}|x,y^{<1>},\ldots,y^{<t-1>})\right]$$

Remark: the parameter α can be seen as a softener, and its value is usually between 0.5 and 1.

❒ **Error analysis** – When obtaining a predicted translation $\widehat{y}$ that is bad, one can wonder why we did not get a good translation y^* by performing the following error analysis:

Case	$P(y^*\|x) > P(\widehat{y}\|x)$	$P(y^*\|x) \leqslant P(\widehat{y}\|x)$
Root cause	Beam search faulty	RNN faulty
Remedies	Increase beam width	- Try different architecture - Regularize - Get more data

❒ **Bleu score** – The bilingual evaluation understudy (bleu) score quantifies how good a machine translation is by computing a similarity score based on n-gram precision. It is defined as follows:

$$\text{bleu score} = \exp\left(\frac{1}{n}\sum_{k=1}^{n} p_k\right)$$

where p_n is the bleu score on n-gram only defined as follows:

$$p_n = \frac{\sum_{\text{n-gram}\in\widehat{y}} \text{count}_{\text{clip}}(\text{n-gram})}{\sum_{\text{n-gram}\in\widehat{y}} \text{count}(\text{n-gram})}$$

Remark: a brevity penalty may be applied to short predicted translations to prevent an artificially inflated bleu score.

Attention

❒ **Attention model** – This model allows an RNN to pay attention to specific parts of the input that is considered as being important, which improves the performance of the resulting model in practice. By noting $\alpha^{<t,t'>}$ the amount of attention that the output $y^{<t>}$ should pay to the activation $a^{<t'>}$ and $c^{<t>}$ the context at time t, we have:

$$\boxed{c^{<t>} = \sum_{t'} \alpha^{<t,t'>} a^{<t'>}} \quad \text{with} \quad \sum_{t'} \alpha^{<t,t'>} = 1$$

Remark: the attention scores are commonly used in image captioning and machine translation.

A cute teddy bear is reading Persian literature

A cute teddy bear is reading Persian literature

❒ **Attention weight** – The amount of attention that the output $y^{<t>}$ should pay to the activation $a^{<t'>}$ is given by $\alpha^{<t,t'>}$ computed as follows:

$$\boxed{\alpha^{<t,t'>} = \frac{\exp(e^{<t,t'>})}{\sum_{t''=1}^{T_x} \exp(e^{<t,t''>})}}$$

Remark: computation complexity is quadratic with respect to T_x.

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Python For Data Science *Cheat Sheet*

PySpark - SQL Basics

Learn Python for data science Interactively at www.DataCamp.com

PySpark & Spark SQL

Spark SQL is Apache Spark's module for working with structured data.

Initializing SparkSession

A SparkSession can be used create DataFrame, register DataFrame as tables, execute SQL over tables, cache tables, and read parquet files.

```
>>> from pyspark.sql import SparkSession
>>> spark = SparkSession \
        .builder \
        .appName("Python Spark SQL basic example") \
        .config("spark.some.config.option", "some-value") \
        .getOrCreate()
```

Creating DataFrames

From RDDs

```
>>> from pyspark.sql.types import *
```

Infer Schema

```
>>> sc = spark.sparkContext
>>> lines = sc.textFile("people.txt")
>>> parts = lines.map(lambda l: l.split(","))
>>> people = parts.map(lambda p: Row(name=p[0],age=int(p[1])))
>>> peopledf = spark.createDataFrame(people)
```

Specify Schema

```
>>> people = parts.map(lambda p: Row(name=p[0],
                                     age=int(p[1].strip())))
>>> schemaString = "name age"
>>> fields = [StructField(field_name, StringType(), True) for
field_name in schemaString.split()]
>>> schema = StructType(fields)
>>> spark.createDataFrame(people, schema).show()
  +--------+---+
  |    name|age|
  +--------+---+
  |    Mine| 28|
  |   Filip| 29|
  |Jonathan| 30|
  +--------+---+
```

From Spark Data Sources

JSON

```
>>> df = spark.read.json("customer.json")
>>> df.show()
  +--------------------+---+---------+--------+--------------------+
  |             address|age|firstName |lastName|         phoneNumber|
  +--------------------+---+---------+--------+--------------------+
  |[New York,10021,N...| 25|     John|   Smith|[[212 555-1234,ho...|
  |[New York,10021,N...| 21|     Jane|     Doe|[[322 888-1234,ho...|
  +--------------------+---+---------+--------+--------------------+
>>> df2 = spark.read.load("people.json", format="json")
```

Parquet files

```
>>> df3 = spark.read.load("users.parquet")
```

TXT files

```
>>> df4 = spark.read.text("people.txt")
```

Duplicate Values

```
>>> df = df.dropDuplicates()
```

Queries

```
>>> from pyspark.sql import functions as F
```

Select

```
>>> df.select("firstName").show()
>>> df.select("firstName","lastName") \
      .show()
>>> df.select("firstName",
              "age",
               explode("phoneNumber") \
              .alias("contactInfo")) \
      .select("contactInfo.type",
              "firstName",
              "age") \
      .show()
```

```
>>> df.select(df["firstName"],df["age"]+ 1)
      .show()
>>> df.select(df['age'] > 24).show()
```

When

```
>>> df.select("firstName",
              F.when(df.age > 30, 1) \
              .otherwise(0)) \
      .show()
>>> df[df.firstName.isin("Jane","Boris")]
                .collect()
```

Like

```
>>> df.select("firstName",
              df.lastName.like("Smith")) \
      .show()
```

Startswith - Endswith

```
>>> df.select("firstName",
              df.lastName \
                .startswith("Sm")) \
      .show()
>>> df.select(df.lastName.endswith("th"))\
      .show()
```

Substring

```
>>> df.select(df.firstName.substr(1, 3) \
                          .alias("name")) \
      .collect()
```

Between

```
>>> df.select(df.age.between(22, 24)) \
      .show()
```

Show all entries in `firstName` column

Show all entries in `firstName`, `age` and `type`

Show all entries in `firstName` and `age`, add `1` to the entries of `age`

Show all entries where `age` >24

Show `firstName` and 0 or 1 depending on `age` >30

Show `firstName` if in the given options

Show `firstName`, and `lastName` is `TRUE` if `lastName` is like `Smith`

Show `firstName`, and `TRUE` if `lastName` starts with `Sm`

Show last names ending in `th`

Return substrings of `firstName`

Show `age`: values are `TRUE` if between 22 and 24

Add, Update & Remove Columns

Adding Columns

```
>>> df = df.withColumn('city',df.address.city) \
           .withColumn('postalCode',df.address.postalCode) \
           .withColumn('state',df.address.state) \
           .withColumn('streetAddress',df.address.streetAddress) \
           .withColumn('telePhoneNumber',
                       explode(df.phoneNumber.number)) \
           .withColumn('telePhoneType',
                       explode(df.phoneNumber.type))
```

Updating Columns

```
>>> df = df.withColumnRenamed('telePhoneNumber', 'phoneNumber')
```

Removing Columns

```
>>> df = df.drop("address", "phoneNumber")
>>> df = df.drop(df.address).drop(df.phoneNumber)
```

Inspect Data

`>>> df.dtypes`	Return `df` column names and data types
`>>> df.show()`	Display the content of `df`
`>>> df.head()`	Return first `n` rows
`>>> df.first()`	Return first row
`>>> df.take(2)`	Return the first `n` rows
`>>> df.schema`	Return the schema of `df`

`>>> df.describe().show()`	Compute summary statistics
`>>> df.columns`	Return the columns of `df`
`>>> df.count()`	Count the number of rows in `df`
`>>> df.distinct().count()`	Count the number of distinct rows in `df`
`>>> df.printSchema()`	Print the schema of `df`
`>>> df.explain()`	Print the (logical and physical) plans

GroupBy

`>>> df.groupBy("age") \ .count() \ .show()`	Group by `age`, count the members in the groups

Filter

`>>> df.filter(df["age"]>24).show()`	Filter entries of `age`, only keep those records of which the values are >24

Sort

```
>>> peopledf.sort(peopledf.age.desc()).collect()
>>> df.sort("age", ascending=False).collect()
>>> df.orderBy(["age","city"],ascending=[0,1])\
      .collect()
```

Missing & Replacing Values

`>>> df.na.fill(50).show()`	Replace null values
`>>> df.na.drop().show()`	Return new `df` omitting rows with null values
`>>> df.na \ .replace(10, 20) \ .show()`	Return new `df` replacing one value with another

Repartitioning

`>>> df.repartition(10)\ .rdd \ .getNumPartitions()`	`df` with 10 partitions
`>>> df.coalesce(1).rdd.getNumPartitions()`	`df` with 1 partition

Running SQL Queries Programmatically

Registering DataFrames as Views

```
>>> peopledf.createGlobalTempView("people")
>>> df.createTempView("customer")
>>> df.createOrReplaceTempView("customer")
```

Query Views

```
>>> df5 = spark.sql("SELECT * FROM customer").show()
>>> peopledf2 = spark.sql("SELECT * FROM global_temp.people")\
                 .show()
```

Output

Data Structures

`>>> rdd1 = df.rdd`	Convert `df` into an RDD
`>>> df.toJSON().first()`	Convert `df` into a RDD of string
`>>> df.toPandas()`	Return the contents of `df` as Pandas `DataFrame`

Write & Save to Files

```
>>> df.select("firstName", "city")\
      .write \
      .save("nameAndCity.parquet")
>>> df.select("firstName", "age") \
      .write \
      .save("namesAndAges.json",format="json")
```

Stopping SparkSession

```
>>> spark.stop()
```

DataCamp
Learn Python for Data Science Interactively

Python For Data Science *Cheat Sheet*

PySpark - RDD Basics

Learn Python for data science Interactively at www.DataCamp.com

Spark

PySpark is the Spark Python API that exposes the Spark programming model to Python.

Initializing Spark

SparkContext

```
>>> from pyspark import SparkContext
>>> sc = SparkContext(master = 'local[2]')
```

Inspect SparkContext

```
>>> sc.version                  Retrieve SparkContext version
>>> sc.pythonVer                Retrieve Python version
>>> sc.master                   Master URL to connect to
>>> str(sc.sparkHome)           Path where Spark is installed on worker nodes
>>> str(sc.sparkUser())         Retrieve name of the Spark User running SparkContext
>>> sc.appName                  Return application name
>>> sc.applicationId            Retrieve application ID
>>> sc.defaultParallelism       Return default level of parallelism
>>> sc.defaultMinPartitions     Default minimum number of partitions for RDDs
```

Configuration

```
>>> from pyspark import SparkConf, SparkContext
>>> conf = (SparkConf()
            .setMaster("local")
            .setAppName("My app")
            .set("spark.executor.memory", "1g"))
>>> sc = SparkContext(conf = conf)
```

Using The Shell

In the PySpark shell, a special interpreter-aware SparkContext is already created in the variable called `sc`.

```
$ ./bin/spark-shell --master local[2]
$ ./bin/pyspark --master local[4] --py-files code.py
```

Set which master the context connects to with the `--master` argument, and add Python .zip, .egg or .py files to the runtime path by passing a comma-separated list to `--py-files`.

Loading Data

Parallelized Collections

```
>>> rdd = sc.parallelize([('a',7),('a',2),('b',2)])
>>> rdd2 = sc.parallelize([('a',2),('d',1),('b',1)])
>>> rdd3 = sc.parallelize(range(100))
>>> rdd4 = sc.parallelize([("a",["x","y","z"]),
                           ("b",["p", "r"])])
```

External Data

Read either one text file from HDFS, a local file system or or any Hadoop-supported file system URI with `textFile()`, or read in a directory of text files with `wholeTextFiles()`.

```
>>> textFile = sc.textFile("/my/directory/*.txt")
>>> textFile2 = sc.wholeTextFiles("/my/directory/")
```

Retrieving RDD Information

Basic Information

```
>>> rdd.getNumPartitions()      List the number of partitions
>>> rdd.count()                 Count RDD instances
 3
>>> rdd.countByKey()            Count RDD instances by key
 defaultdict(<type 'int'>,{'a':2,'b':1})
>>> rdd.countByValue()          Count RDD instances by value
 defaultdict(<type 'int'>,{('b',2):1,('a',2):1,('a',7):1})
>>> rdd.collectAsMap()          Return (key,value) pairs as a dictionary
 {'a': 2,'b': 2}
>>> rdd3.sum()                  Sum of RDD elements
 4950
>>> sc.parallelize([]).isEmpty()  Check whether RDD is empty
  True
```

Summary

```
>>> rdd3.max()                  Maximum value of RDD elements
  99
>>> rdd3.min()                  Minimum value of RDD elements
  0
>>> rdd3.mean()                 Mean value of RDD elements
  49.5
>>> rdd3.stdev()                Standard deviation of RDD elements
  28.866070047722118
>>> rdd3.variance()             Compute variance of RDD elements
  833.25
>>> rdd3.histogram(3)           Compute histogram by bins
  ([0,33,66,99],[33,33,34])
>>> rdd3.stats()                Summary statistics (count, mean, stdev, max & min)
```

Applying Functions

```
>>> rdd.map(lambda x: x+(x[1],x[0]))   Apply a function to each RDD element
       .collect()
  [('a',7,7,'a'),('a',2,2,'a'),('b',2,2,'b')]
>>> rdd5 = rdd.flatMap(lambda x: x+(x[1],x[0]))   Apply a function to each RDD element and flatten the result

>>> rdd5.collect()
  ['a',7,7,'a','a',2,2,'a','b',2,2,'b']
>>> rdd4.flatMapValues(lambda x: x)   Apply a flatMap function to each (key,value) pair of rdd4 without changing the keys
       .collect()
  [('a','x'),('a','y'),('a','z'),('b','p'),('b','r')]
```

Selecting Data

Getting

```
>>> rdd.collect()               Return a list with all RDD elements
  [('a', 7), ('a', 2), ('b', 2)]
>>> rdd.take(2)                 Take first 2 RDD elements
  [('a', 7), ('a', 2)]
>>> rdd.first()                 Take first RDD element
  ('a', 7)
>>> rdd.top(2)                  Take top 2 RDD elements
  [('b', 2), ('a', 7)]
```

Sampling

```
>>> rdd3.sample(False, 0.15, 81).collect()   Return sampled subset of rdd3
  [3,4,27,31,40,41,42,43,60,76,79,80,86,97]
```

Filtering

```
>>> rdd.filter(lambda x: "a" in x)   Filter the RDD
       .collect()
  [('a',7),('a',2)]
>>> rdd5.distinct().collect()   Return distinct RDD values
  ['a',2,'b',7]
>>> rdd.keys().collect()        Return (key,value) RDD's keys
  ['a', 'a', 'b']
```

Iterating

```
>>> def g(x): print(x)
>>> rdd.foreach(g)              Apply a function to all RDD elements
  ('a', 7)
  ('b', 2)
  ('a', 2)
```

Reshaping Data

Reducing

```
>>> rdd.reduceByKey(lambda x,y : x+y)   Merge the rdd values for each key
       .collect()
  [('a',9),('b',2)]
>>> rdd.reduce(lambda a, b: a + b)   Merge the rdd values
  ('a',7,'a',2,'b',2)
```

Grouping by

```
>>> rdd3.groupBy(lambda x: x % 2)   Return RDD of grouped values
        .mapValues(list)
        .collect()
>>> rdd.groupByKey()            Group rdd by key
        .mapValues(list)
        .collect()
  [('a',[7,2]),('b',[2])]
```

Aggregating

```
>>> seqOp = (lambda x,y: (x[0]+y,x[1]+1))
>>> combOp = (lambda x,y:(x[0]+y[0],x[1]+y[1]))
>>> rdd3.aggregate((0,0),seqOp,combOp)   Aggregate RDD elements of each partition and then the results
  (4950,100)
>>> rdd.aggregateByKey((0,0),seqop,combop)   Aggregate values of each RDD key
        .collect()
  [('a',(9,2)), ('b',(2,1))]
>>> rdd3.fold(0,add)            Aggregate the elements of each partition, and then the results
 4950
>>> rdd.foldByKey(0, add)       Merge the values for each key
        .collect()
  [('a',9),('b',2)]
>>> rdd3.keyBy(lambda x: x+x)   Create tuples of RDD elements by applying a function
        .collect()
```

Mathematical Operations

```
>>> rdd.subtract(rdd2)          Return each rdd value not contained in rdd2
       .collect()
  [('b',2),('a',7)]
>>> rdd2.subtractByKey(rdd)     Return each (key,value) pair of rdd2 with no matching key in rdd
       .collect()
  [('d', 1)]
>>> rdd.cartesian(rdd2).collect()   Return the Cartesian product of rdd and rdd2
```

Sort

```
>>> rdd2.sortBy(lambda x: x[1])   Sort RDD by given function
       .collect()
  [('d',1),('b',1),('a',2)]
>>> rdd2.sortByKey()            Sort (key, value) RDD by key
       .collect()
  [('a',2),('b',1),('d',1)]
```

Repartitioning

```
>>> rdd.repartition(4)          New RDD with 4 partitions
>>> rdd.coalesce(1)             Decrease the number of partitions in the RDD to 1
```

Saving

```
>>> rdd.saveAsTextFile("rdd.txt")
>>> rdd.saveAsHadoopFile("hdfs://namenodehost/parent/child",
                         'org.apache.hadoop.mapred.TextOutputFormat')
```

Stopping SparkContext

```
>>> sc.stop()
```

Execution

```
$ ./bin/spark-submit examples/src/main/python/pi.py
```

Python For Data Science *Cheat Sheet*

SciPy - Linear Algebra

Learn More Python for Data Science Interactively at www.datacamp.com

SciPy

The **SciPy** library is one of the core packages for scientific computing that provides mathematical algorithms and convenience functions built on the NumPy extension of Python.

Interacting With NumPy

Also see NumPy

```
>>> import numpy as np
>>> a = np.array([1,2,3])
>>> b = np.array([(1+5j,2j,3j), (4j,5j,6j)])
>>> c = np.array([[(1.5,2,3), (4,5,6)], [(3,2,1), (4,5,6)]])
```

Index Tricks

```
>>> np.mgrid[0:5,0:5]
>>> np.ogrid[0:2,0:2]
>>> np.r_[[3,[0]*5,-1:1:10j]
>>> np.c_[b,c]
```

Create a dense meshgrid
Create an open meshgrid
Stack arrays vertically (row-wise)
Create stacked column-wise arrays

Shape Manipulation

```
>>> np.transpose(b)
>>> b.flatten()
>>> np.hstack((b,c))
>>> np.vstack((a,b))
>>> np.hsplit(c,2)
>>> np.vpslit(d,2)
```

Permute array dimensions
Flatten the array
Stack arrays horizontally (column-wise)
Stack arrays vertically (row-wise)
Split the array horizontally at the 2nd index
Split the array vertically at the 2nd index

Polynomials

```
>>> from numpy import poly1d
>>> p = poly1d([3,4,5])
```

Create a polynomial object

Vectorizing Functions

```
>>> def myfunc(a):
        if a < 0:
          return a*2
        else:
          return a/2
>>> np.vectorize(myfunc)
```

Vectorize functions

Type Handling

```
>>> np.real(c)
>>> np.imag(c)
>>> np.real_if_close(c,tol=1000)
>>> np.cast['f'](np.pi)
```

Return the real part of the array elements
Return the imaginary part of the array elements
Return a real array if complex parts close to 0
Cast object to a data type

Other Useful Functions

```
>>> np.angle(b,deg=True)
>>> g = np.linspace(0,np.pi,num=5)
>>> g [3:] += np.pi
>>> np.unwrap(g)
>>> np.logspace(0,10,3)
>>> np.select([c<4],[c*2])
>>> misc.factorial(a)
>>> misc.comb(10,3,exact=True)
>>> misc.central_diff_weights(3)
>>> misc.derivative(myfunc,1.0)
```

Return the angle of the complex argument
Create an array of evenly spaced values (number of samples)
Unwrap
Create an array of evenly spaced values (log scale)
Return values from a list of arrays depending on conditions
Factorial
Combine N things taken at k time
Weights for Np-point central derivative
Find the n-th derivative of a function at a point

Linear Algebra

Also see NumPy

You'll use the `linalg` and `sparse` modules. Note that `scipy.linalg` contains and expands on `numpy.linalg`.

```
>>> from scipy import linalg, sparse
```

Creating Matrices

```
>>> A = np.matrix(np.random.random((2,2)))
>>> B = np.asmatrix(b)
>>> C = np.mat(np.random.random((10,5)))
>>> D = np.mat([[3,4], [5,6]])
```

Basic Matrix Routines

Inverse

```
>>> A.I
>>> linalg.inv(A)
```

Inverse
Inverse

Transpose

```
>>> A.T
```

Tranpose matrix

Conjugate transposition

```
>>> A.H
```

Conjugate transposition

Trace

```
>>> np.trace(A)
```

Trace

Norm

```
>>> linalg.norm(A)
>>> linalg.norm(A,1)
>>> linalg.norm(A,np.inf)
```

Frobenius norm
L1 norm (max column sum)
L inf norm (max row sum)

Rank

```
>>> np.linalg.matrix_rank(C)
```

Matrix rank

Determinant

```
>>> linalg.det(A)
```

Determinant

Solving linear problems

```
>>> linalg.solve(A,b)
>>> E = np.mat(a).T
>>> linalg.lstsq(D,E)
```

Solver for dense matrices
Solver for dense matrices
Least-squares solution to linear matrix equation

Generalized inverse

```
>>> linalg.pinv(C)
>>> linalg.pinv2(C)
```

Compute the pseudo-inverse of a matrix (least-squares solver)
Compute the pseudo-inverse of a matrix (SVD)

Creating Sparse Matrices

```
>>> F = np.eye(3, k=1)
>>> G = np.mat(np.identity(2))
>>> C[C > 0.5] = 0
>>> H = sparse.csr_matrix(C)
>>> I = sparse.csc_matrix(D)
>>> J = sparse.dok_matrix(A)
>>> E.todense()
>>> sparse.isspmatrix_csc(A)
```

Create a 2X2 identity matrix
Create a 2x2 identity matrix
Compressed Sparse Row matrix
Compressed Sparse Column matrix
Dictionary Of Keys matrix
Sparse matrix to full matrix
Identify sparse matrix

Sparse Matrix Routines

Inverse

```
>>> sparse.linalg.inv(I)
```

Inverse

Norm

```
>>> sparse.linalg.norm(I)
```

Norm

Solving linear problems

```
>>> sparse.linalg.spsolve(H,I)
```

Solver for sparse matrices

Sparse Matrix Functions

```
>>> sparse.linalg.expm(I)
```

Sparse matrix exponential

Matrix Functions

Addition

```
>>> np.add(A,D)
```

Addition

Subtraction

```
>>> np.subtract(A,D)
```

Subtraction

Division

```
>>> np.divide(A,D)
```

Division

Multiplication

```
>>> np.multiply(D,A)
>>> np.dot(A,D)
>>> np.vdot(A,D)
>>> np.inner(A,D)
>>> np.outer(A,D)
>>> np.tensordot(A,D)
>>> np.kron(A,D)
```

Multiplication
Dot product
Vector dot product
Inner product
Outer product
Tensor dot product
Kronecker product

Exponential Functions

```
>>> linalg.expm(A)
>>> linalg.expm2(A)
>>> linalg.expm3(D)
```

Matrix exponential
Matrix exponential (Taylor Series)
Matrix exponential (eigenvalue decomposition)

Logarithm Function

```
>>> linalg.logm(A)
```

Matrix logarithm

Trigonometric Tunctions

```
>>> linalg.sinm(D)
>>> linalg.cosm(D)
>>> linalg.tanm(A)
```

Matrix sine
Matrix cosine
Matrix tangent

Hyperbolic Trigonometric Functions

```
>>> linalg.sinhm(D)
>>> linalg.coshm(D)
>>> linalg.tanhm(A)
```

Hypberbolic matrix sine
Hyperbolic matrix cosine
Hyperbolic matrix tangent

Matrix Sign Function

```
>>> np.sigm(A)
```

Matrix sign function

Matrix Square Root

```
>>> linalg.sqrtm(A)
```

Matrix square root

Arbitrary Functions

```
>>> linalg.funm(A, lambda x: x*x)
```

Evaluate matrix function

Decompositions

Eigenvalues and Eigenvectors

```
>>> la, v = linalg.eig(A)
>>> l1, l2 = la
>>> v[:,0]
>>> v[:,1]
>>> linalg.eigvals(A)
```

Solve ordinary or generalized eigenvalue problem for square matrix
Unpack eigenvalues
First eigenvector
Second eigenvector
Unpack eigenvalues

Singular Value Decomposition

```
>>> U,s,Vh = linalg.svd(B)
>>> M,N = B.shape
>>> Sig = linalg.diagsvd(s,M,N)
```

Singular Value Decomposition (SVD)
Construct sigma matrix in SVD

LU Decomposition

```
>>> P,L,U = linalg.lu(C)
```

LU Decomposition

Sparse Matrix Decompositions

```
>>> la, v = sparse.linalg.eigs(F,1)
>>> sparse.linalg.svds(H, 2)
```

Eigenvalues and eigenvectors
SVD

Asking For Help

```
>>> help(scipy.linalg.diagsvd)
>>> np.info(np.matrix)
```

Python For Data Science *Cheat Sheet*

Matplotlib

Learn Python Interactively at www.DataCamp.com

Matplotlib

Matplotlib is a Python 2D plotting library which produces publication-quality figures in a variety of hardcopy formats and interactive environments across platforms.

matplotlib

1 Prepare The Data

Also see Lists & NumPy

1D Data

```
>>> import numpy as np
>>> x = np.linspace(0, 10, 100)
>>> y = np.cos(x)
>>> z = np.sin(x)
```

2D Data or Images

```
>>> data = 2 * np.random.random((10, 10))
>>> data2 = 3 * np.random.random((10, 10))
>>> Y, X = np.mgrid[-3:3:100j, -3:3:100j]
>>> U = -1 - X**2 + Y
>>> V = 1 + X - Y**2
>>> from matplotlib.cbook import get_sample_data
>>> img = np.load(get_sample_data('axes_grid/bivariate_normal.npy'))
```

2 Create Plot

```
>>> import matplotlib.pyplot as plt
```

Figure

```
>>> fig = plt.figure()
>>> fig2 = plt.figure(figsize=plt.figaspect(2.0))
```

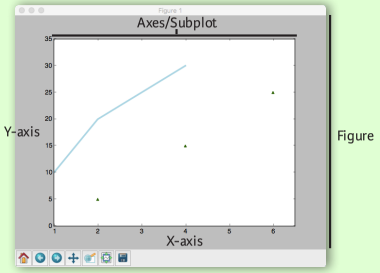
Axes

All plotting is done with respect to an `Axes`. In most cases, a subplot will fit your needs. A subplot is an axes on a grid system.

```
>>> fig.add_axes()
>>> ax1 = fig.add_subplot(221) # row-col-num
>>> ax3 = fig.add_subplot(212)
>>> fig3, axes = plt.subplots(nrows=2,ncols=2)
>>> fig4, axes2 = plt.subplots(ncols=3)
```

Plot Anatomy & Workflow

Plot Anatomy



Workflow

The basic steps to creating plots with matplotlib are:

1 Prepare data 2 Create plot 3 Plot 4 Customize plot 5 Save plot 6 Show plot

```
>>> import matplotlib.pyplot as plt
>>> x = [1,2,3,4]                          Step 1
>>> y = [10,20,25,30]
>>> fig = plt.figure()                     Step 2
>>> ax = fig.add_subplot(111)              Step 3
>>> ax.plot(x, y, color='lightblue', linewidth=3)   Step 3, 4
>>> ax.scatter([2,4,6],
               [5,15,25],
               color='darkgreen',
               marker='^')
>>> ax.set_xlim(1, 6.5)
>>> plt.savefig('foo.png')
>>> plt.show()                             Step 6
```

4 Customize Plot

Colors, Color Bars & Color Maps

```
>>> plt.plot(x, x, x, x**2, x, x**3)
>>> ax.plot(x, y, alpha = 0.4)
>>> ax.plot(x, y, c='k')
>>> fig.colorbar(im, orientation='horizontal')
>>> im = ax.imshow(img,
                   cmap='seismic')
```

Markers

```
>>> fig, ax = plt.subplots()
>>> ax.scatter(x,y,marker=".")
>>> ax.plot(x,y,marker="o")
```

Linestyles

```
>>> plt.plot(x,y,linewidth=4.0)
>>> plt.plot(x,y,ls='solid')
>>> plt.plot(x,y,ls='--')
>>> plt.plot(x,y,'--',x**2,y**2,'-.')
>>> plt.setp(lines,color='r',linewidth=4.0)
```

Text & Annotations

```
>>> ax.text(1,
            -2.1,
            'Example Graph',
            style='italic')
>>> ax.annotate("Sine",
                xy=(8, 0),
                xycoords='data',
                xytext=(10.5, 0),
                textcoords='data',
                arrowprops=dict(arrowstyle="->",
                                connectionstyle="arc3"),)
```

Mathtext

```
>>> plt.title(r'$sigma_i=15$', fontsize=20)
```

Limits, Legends & Layouts

Limits & Autoscaling

```
>>> ax.margins(x=0.0,y=0.1)                 Add padding to a plot
>>> ax.axis('equal')                        Set the aspect ratio of the plot to 1
>>> ax.set(xlim=[0,10.5],ylim=[-1.5,1.5])   Set limits for x-and y-axis
>>> ax.set_xlim(0,10.5)                     Set limits for x-axis
```

Legends

```
>>> ax.set(title='An Example Axes',         Set a title and x-and y-axis labels
           ylabel='Y-Axis',
           xlabel='X-Axis')
>>> ax.legend(loc='best')                   No overlapping plot elements
```

Ticks

```
>>> ax.xaxis.set(ticks=range(1,5),          Manually set x-ticks
                 ticklabels=[3,100,-12,"foo"])
>>> ax.tick_params(axis='y',                Make y-ticks longer and go in and out
                   direction='inout',
                   length=10)
```

Subplot Spacing

```
>>> fig3.subplots_adjust(wspace=0.5,        Adjust the spacing between subplots
                         hspace=0.3,
                         left=0.125,
                         right=0.9,
                         top=0.9,
                         bottom=0.1)
>>> fig.tight_layout()                      Fit subplot(s) in to the figure area
```

Axis Spines

```
>>> ax1.spines['top'].set_visible(False)    Make the top axis line for a plot invisible
>>> ax1.spines['bottom'].set_position(('outward',10))   Move the bottom axis line outward
```

3 Plotting Routines

1D Data

```
>>> fig, ax = plt.subplots()
>>> lines = ax.plot(x,y)                    Draw points with lines or markers connecting them
>>> ax.scatter(x,y)                         Draw unconnected points, scaled or colored
>>> axes[0,0].bar([1,2,3],[3,4,5])          Plot vertical rectangles (constant width)
>>> axes[1,0].barh([0.5,1,2.5],[0,1,2])     Plot horiontal rectangles (constant height)
>>> axes[1,1].axhline(0.45)                 Draw a horizontal line across axes
>>> axes[0,1].axvline(0.65)                 Draw a vertical line across axes
>>> ax.fill(x,y,color='blue')               Draw filled polygons
>>> ax.fill_between(x,y,color='yellow')     Fill between y-values and 0
```

Vector Fields

```
>>> axes[0,1].arrow(0,0,0.5,0.5)            Add an arrow to the axes
>>> axes[1,1].quiver(y,z)                   Plot a 2D field of arrows
>>> axes[0,1].streamplot(X,Y,U,V)           Plot a 2D field of arrows
```

Data Distributions

```
>>> ax1.hist(y)                             Plot a histogram
>>> ax3.boxplot(y)                          Make a box and whisker plot
>>> ax3.violinplot(z)                       Make a violin plot
```

2D Data or Images

```
>>> fig, ax = plt.subplots()
>>> im = ax.imshow(img,                     Colormapped or RGB arrays
                   cmap='gist_earth',
                   interpolation='nearest',
                   vmin=-2,
                   vmax=2)
```

```
>>> axes2[0].pcolor(data2)                  Pseudocolor plot of 2D array
>>> axes2[0].pcolormesh(data)               Pseudocolor plot of 2D array
>>> CS = plt.contour(Y,X,U)                 Plot contours
>>> axes2[2].contourf(data1)                Plot filled contours
>>> axes2[2]= ax.clabel(CS)                 Label a contour plot
```

5 Save Plot

Save figures

```
>>> plt.savefig('foo.png')
```

Save transparent figures

```
>>> plt.savefig('foo.png', transparent=True)
```

6 Show Plot

```
>>> plt.show()
```

Close & Clear

```
>>> plt.cla()                               Clear an axis
>>> plt.clf()                               Clear the entire figure
>>> plt.close()                             Close a window
```

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Learn Python for Data Science Interactively

Matplotlib 2.0.0 - Updated on 8-2017

Python For Data Science *Cheat Sheet*

Seaborn

Learn Data Science Interactively at www.DataCamp.com

Statistical Data Visualization With Seaborn

The Python visualization library **Seaborn** is based on matplotlib and provides a high-level interface for drawing attractive statistical graphics.

Make use of the following aliases to import the libraries:

```
>>> import matplotlib.pyplot as plt
>>> import seaborn as sns
```

The basic steps to creating plots with Seaborn are:

1. Prepare some data
2. Control figure aesthetics
3. Plot with Seaborn
4. Further customize your plot

```
>>> import matplotlib.pyplot as plt
>>> import seaborn as sns
>>> tips = sns.load_dataset("tips")                    Step 1
>>> sns.set_style("whitegrid")                         Step 2
>>> g = sns.lmplot(x="tip",                            Step 3
                   y="total_bill",
                   data=tips,
                   aspect=2)
>>> g = (g.set_axis_labels("Tip","Total bill(USD)").
set(xlim=(0,10),ylim=(0,100)))                         Step 4
>>> plt.title("title")
>>> plt.show(g)                                        Step 5
```

1 Data

Also see Lists, NumPy & Pandas

```
>>> import pandas as pd
>>> import numpy as np
>>> uniform_data = np.random.rand(10, 12)
>>> data = pd.DataFrame({'x':np.arange(1,101),
                         'y':np.random.normal(0,4,100)})
```

Seaborn also offers built-in data sets:

```
>>> titanic = sns.load_dataset("titanic")
>>> iris = sns.load_dataset("iris")
```

2 Figure Aesthetics

Also see Matplotlib

`>>> f, ax = plt.subplots(figsize=(5,6))`	Create a figure and one subplot

Seaborn styles

`>>> sns.set()`	(Re)set the seaborn default
`>>> sns.set_style("whitegrid")`	Set the matplotlib parameters
`>>> sns.set_style("ticks", {"xtick.major.size":8, "ytick.major.size":8})`	Set the matplotlib parameters
`>>> sns.axes_style("whitegrid")`	Return a dict of params or use with `with` to temporarily set the style

Context Functions

`>>> sns.set_context("talk")`	Set context to `"talk"`
`>>> sns.set_context("notebook", font_scale=1.5, rc={"lines.linewidth":2.5})`	Set context to `"notebook"`, scale font elements and override param mapping

Color Palette

`>>> sns.set_palette("husl",3)`	Define the color palette
`>>> sns.color_palette("husl")`	Use with `with` to temporarily set palette
`>>> flatui = ["#9b59b6","#3498db","#95a5a6","#e74c3c","#34495e","#2ecc71"]`	
`>>> sns.set_palette(flatui)`	Set your own color palette

3 Plotting With Seaborn

Axis Grids

`>>> g = sns.FacetGrid(titanic, col="survived", row="sex")`	Subplot grid for plotting conditional relationships
`>>> g = g.map(plt.hist,"age")`	
`>>> sns.factorplot(x="pclass", y="survived", hue="sex", data=titanic)`	Draw a categorical plot onto a Facetgrid
`>>> sns.lmplot(x="sepal_width", y="sepal_length", hue="species", data=iris)`	Plot data and regression model fits across a FacetGrid
`>>> h = sns.PairGrid(iris)`	Subplot grid for plotting pairwise relationships
`>>> h = h.map(plt.scatter)`	
`>>> sns.pairplot(iris)`	Plot pairwise bivariate distributions
`>>> i = sns.JointGrid(x="x", y="y", data=data)`	Grid for bivariate plot with marginal univariate plots
`>>> i = i.plot(sns.regplot, sns.distplot)`	
`>>> sns.jointplot("sepal_length", "sepal_width", data=iris, kind='kde')`	Plot bivariate distribution

Categorical Plots

Scatterplot

`>>> sns.stripplot(x="species", y="petal_length", data=iris)`	Scatterplot with one categorical variable
`>>> sns.swarmplot(x="species", y="petal_length", data=iris)`	Categorical scatterplot with non-overlapping points

Bar Chart

`>>> sns.barplot(x="sex", y="survived", hue="class", data=titanic)`	Show point estimates and confidence intervals with scatterplot glyphs

Count Plot

`>>> sns.countplot(x="deck", data=titanic, palette="Greens_d")`	Show count of observations

Point Plot

`>>> sns.pointplot(x="class", y="survived", hue="sex", data=titanic, palette={"male":"g", "female":"m"}, markers=["^","o"], linestyles=["-","--"])`	Show point estimates and confidence intervals as rectangular bars

Boxplot

`>>> sns.boxplot(x="alive", y="age", hue="adult_male", data=titanic)`	Boxplot
`>>> sns.boxplot(data=iris,orient="h")`	Boxplot with wide-form data

Violinplot

`>>> sns.violinplot(x="age", y="sex", hue="survived", data=titanic)`	Violin plot

Regression Plots

`>>> sns.regplot(x="sepal_width", y="sepal_length", data=iris, ax=ax)`	Plot data and a linear regression model fit

Distribution Plots

`>>> plot = sns.distplot(data.y, kde=False, color="b")`	Plot univariate distribution

Matrix Plots

`>>> sns.heatmap(uniform_data,vmin=0,vmax=1)`	Heatmap

4 Further Customizations

Also see Matplotlib

Axisgrid Objects

`>>> g.despine(left=True)`	Remove left spine
`>>> g.set_ylabels("Survived")`	Set the labels of the y-axis
`>>> g.set_xticklabels(rotation=45)`	Set the tick labels for x
`>>> g.set_axis_labels("Survived", "Sex")`	Set the axis labels
`>>> h.set(xlim=(0,5), ylim=(0,5), xticks=[0,2.5,5], yticks=[0,2.5,5])`	Set the limit and ticks of the x-and y-axis

Plot

`>>> plt.title("A Title")`	Add plot title
`>>> plt.ylabel("Survived")`	Adjust the label of the y-axis
`>>> plt.xlabel("Sex")`	Adjust the label of the x-axis
`>>> plt.ylim(0,100)`	Adjust the limits of the y-axis
`>>> plt.xlim(0,10)`	Adjust the limits of the x-axis
`>>> plt.setp(ax,yticks=[0,5])`	Adjust a plot property
`>>> plt.tight_layout()`	Adjust subplot params

5 Show or Save Plot

Also see Matplotlib

`>>> plt.show()`	Show the plot
`>>> plt.savefig("foo.png")`	Save the plot as a figure
`>>> plt.savefig("foo.png", transparent=True)`	Save transparent figure

Close & Clear

Also see Matplotlib

`>>> plt.cla()`	Clear an axis
`>>> plt.clf()`	Clear an entire figure
`>>> plt.close()`	Close a window

Python For Data Science *Cheat Sheet*

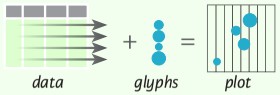
Bokeh

Learn Bokeh Interactively at www.DataCamp.com, taught by Bryan Van de Ven, core contributor

Plotting With Bokeh

The Python interactive visualization library **Bokeh** enables high-performance visual presentation of large datasets in modern web browsers.

Bokeh's mid-level general purpose `bokeh.plotting` interface is centered around two main components: data and glyphs.



The basic steps to creating plots with the `bokeh.plotting` interface are:

1. Prepare some data:

Python lists, NumPy arrays, Pandas DataFrames and other sequences of values

2. Create a new plot
3. Add renderers for your data, with visual customizations
4. Specify where to generate the output
5. Show or save the results

```
>>> from bokeh.plotting import figure
>>> from bokeh.io import output_file, show
>>> x = [1, 2, 3, 4, 5]                          Step 1
>>> y = [6, 7, 2, 4, 5]
>>> p = figure(title="simple line example",      Step 2
              x_axis_label='x',
              y_axis_label='y')
>>> p.line(x, y, legend="Temp.", line_width=2)   Step 3
>>> output_file("lines.html")                    Step 4
>>> show(p)                                      Step 5
```

1 Data

Also see Lists, NumPy & Pandas

Under the hood, your data is converted to Column Data Sources. You can also do this manually:

```
>>> import numpy as np
>>> import pandas as pd
>>> df = pd.DataFrame(np.array([[33.9,4,65, 'US'],
                                [32.4,4,66, 'Asia'],
                                [21.4,4,109, 'Europe']]),
                      columns=['mpg','cyl', 'hp', 'origin'],
                      index=['Toyota', 'Fiat', 'Volvo'])
```

```
>>> from bokeh.models import ColumnDataSource
>>> cds_df = ColumnDataSource(df)
```

2 Plotting

```
>>> from bokeh.plotting import figure
>>> p1 = figure(plot_width=300, tools='pan,box_zoom')
>>> p2 = figure(plot_width=300, plot_height=300,
               x_range=(0, 8), y_range=(0, 8))
>>> p3 = figure()
```

3 Renderers & Visual Customizations

Glyphs

Scatter Markers

```
>>> p1.circle(np.array([1,2,3]), np.array([3,2,1]),
              fill_color='white')
>>> p2.square(np.array([1.5,3.5,5.5]), [1,4,3],
              color='blue', size=1)
```

Line Glyphs

```
>>> p1.line([1,2,3,4], [3,4,5,6], line_width=2)
>>> p2.multi_line(pd.DataFrame([[1,2,3],[5,6,7]]),
                  pd.DataFrame([[3,4,5],[3,2,1]]),
                  color="blue")
```

Customized Glyphs

Also see Data

Selection and Non-Selection Glyphs

```
>>> p = figure(tools='box_select')
>>> p.circle('mpg', 'cyl', source=cds_df,
             selection_color='red',
             nonselection_alpha=0.1)
```

Hover Glyphs

```
>>> from bokeh.models import HoverTool
>>> hover = HoverTool(tooltips=None, mode='vline')
>>> p3.add_tools(hover)
```

Colormapping

```
>>> from bokeh.models import CategoricalColorMapper
>>> color_mapper = CategoricalColorMapper(
                   factors=['US', 'Asia', 'Europe'],
                   palette=['blue', 'red', 'green'])
>>> p3.circle('mpg', 'cyl', source=cds_df,
              color=dict(field='origin',
                         transform=color_mapper),
              legend='Origin')
```

Legend Location

Inside Plot Area

```
>>> p.legend.location = 'bottom_left'
```

Outside Plot Area

```
>>> from bokeh.models import Legend
>>> r1 = p2.asterisk(np.array([1,2,3]), np.array([3,2,1])
>>> r2 = p2.line([1,2,3,4], [3,4,5,6])
>>> legend = Legend(items=[("One" ,[p1, r1]),("Two",[r2])],
                    location=(0, -30))
>>> p.add_layout(legend, 'right')
```

Legend Orientation

```
>>> p.legend.orientation = "horizontal"
>>> p.legend.orientation = "vertical"
```

Legend Background & Border

```
>>> p.legend.border_line_color = "navy"
>>> p.legend.background_fill_color = "white"
```

Rows & Columns Layout

Rows

```
>>> from bokeh.layouts import row
>>> layout = row(p1,p2,p3)
```

Columns

```
>>> from bokeh.layouts import columns
>>> layout = column(p1,p2,p3)
```

Nesting Rows & Columns

```
>>>layout = row(column(p1,p2), p3)
```

Grid Layout

```
>>> from bokeh.layouts import gridplot
>>> row1 = [p1,p2]
>>> row2 = [p3]
>>> layout = gridplot([[p1,p2],[p3]])
```

Tabbed Layout

```
>>> from bokeh.models.widgets import Panel, Tabs
>>> tab1 = Panel(child=p1, title="tab1")
>>> tab2 = Panel(child=p2, title="tab2")
>>> layout = Tabs(tabs=[tab1, tab2])
```

Linked Plots

Linked Axes

```
>>> p2.x_range = p1.x_range
>>> p2.y_range = p1.y_range
```

Linked Brushing

```
>>> p4 = figure(plot_width = 100,
                tools='box_select,lasso_select')
>>> p4.circle('mpg', 'cyl', source=cds_df)
>>> p5 = figure(plot_width = 200,
                tools='box_select,lasso_select')
>>> p5.circle('mpg', 'hp', source=cds_df)
>>> layout = row(p4,p5)
```

4 Output & Export

Notebook

```
>>> from bokeh.io import output_notebook, show
>>> output_notebook()
```

HTML

Standalone HTML

```
>>> from bokeh.embed import file_html
>>> from bokeh.resources import CDN
>>> html = file_html(p, CDN, "my_plot")
```

```
>>> from bokeh.io import output_file, show
>>> output_file('my_bar_chart.html', mode='cdn')
```

Components

```
>>> from bokeh.embed import components
>>> script, div = components(p)
```

PNG

```
>>> from bokeh.io import export_png
>>> export_png(p, filename="plot.png")
```

SVG

```
>>> from bokeh.io import export_svgs
>>> p.output_backend = "svg"
>>> export_svgs(p, filename="plot.svg")
```

5 Show or Save Your Plots

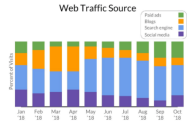
```
>>> show(p1)
>>> save(p1)
```

```
>>> show(layout)
>>> save(layout)
```

Exploration and Visualization

The type of dashboard you should use depends on what you'll be using it for.

Common Dashboard Elements

Type	What is it best for?	Example
Time series	Tracking a value over time	
Stacked bar chart	Tracking composition over time	
Bar chart	Categorical comparison	

Popular Dashboard Tools

Spreadsheets	BI Tools	Customized Tools
Excel	Power BI	R Shiny
Sheets	Tableau	d3.js
	Looker	

When You Should Request a Dashboard

- When you'll use it multiple times
- When you'll need the information updated regularly
- When the request will always be the same

Experimentation and Prediction

Machine Learning

Machine learning is an application of artificial intelligence (AI) that builds algorithms and statistical models to train data to address specific questions without explicit instructions.

	Supervised Machine Learning	Unsupervised Machine Learning
Purpose	Makes predictions from data with labels and features	Makes predictions by clustering data with no labels into categories
Example	Recommendation systems, email subject optimization, churn prediction	Image segmentation, customer segmentation
		

Special Topics in Machine Learning

- **Time Series Forecasting** is a technique for predicting events through a sequence of time and can capture seasonality or periodic events.
- **Natural Language Processing (NLP)** allows computers to process and analyze large amounts of natural language data.
  - Text as input data
  - Word counts track the important words in a text
  - Word embeddings create features that group similar words

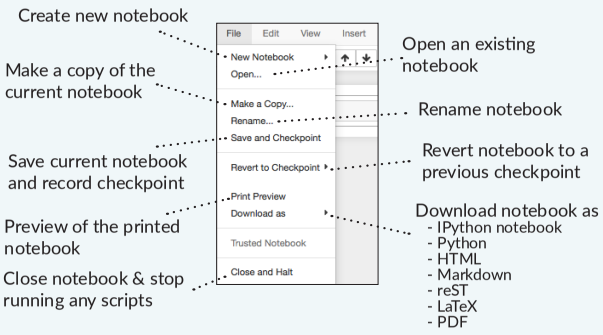
Deep Learning / Neural Networks enables unsupervised machine learning using data that is unstructured or unlabeled.	**Explainable AI** is an emerging field in machine learning that applies AI such that results can be easily understood.
Highly accurate predictions	Understandable by humans
Better for "What?"	Better for "Why?"

Python For Data Science *Cheat Sheet*

Jupyter Notebook

Learn More Python for Data Science Interactively at www.DataCamp.com

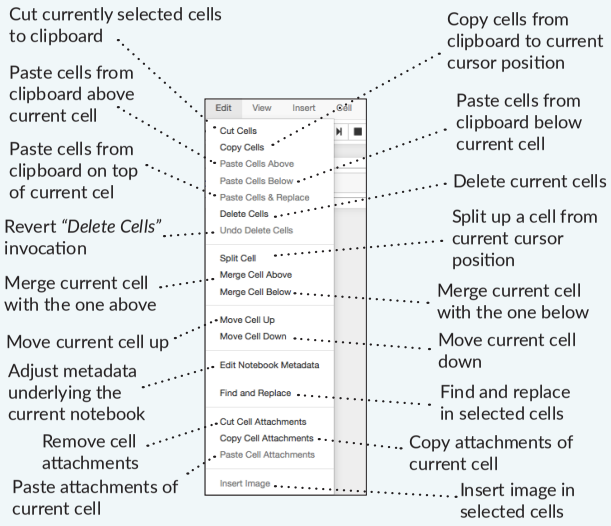
Saving/Loading Notebooks



Writing Code And Text

Code and text are encapsulated by 3 basic cell types: markdown cells, code cells, and raw NBConvert cells.

Edit Cells



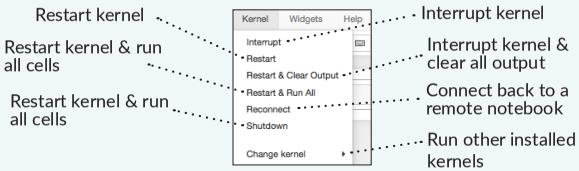
Insert Cells

Working with Different Programming Languages

Kernels provide computation and communication with front-end interfaces like the notebooks. There are three main kernels:

IPython | IRkernel | IJulia

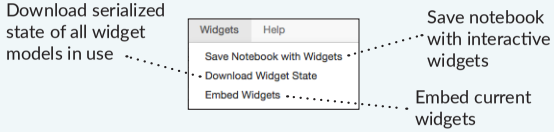
Installing Jupyter Notebook will automatically install the IPython kernel.



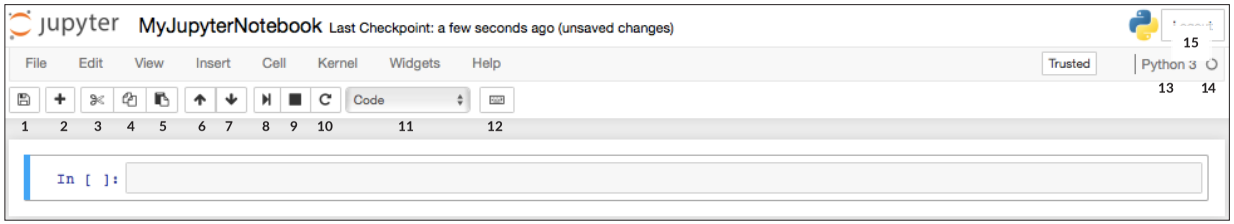
Widgets

Notebook widgets provide the ability to visualize and control changes in your data, often as a control like a slider, textbox, etc.

You can use them to build interactive GUIs for your notebooks or to synchronize stateful and stateless information between Python and JavaScript.



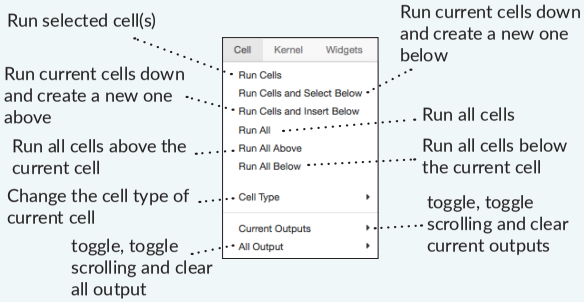
Command Mode:



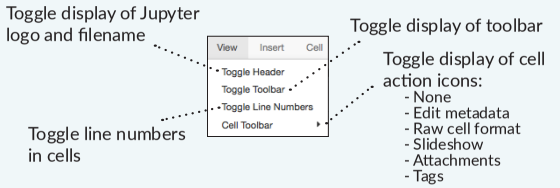
Edit Mode:

1. Save and checkpoint
2. Insert cell below
3. Cut cell
4. Copy cell(s)
5. Paste cell(s) below
6. Move cell up
7. Move cell down
8. Run current cell
9. Interrupt kernel
10. Restart kernel
11. Display characteristics
12. Open command palette
13. Current kernel
14. Kernel status
15. Log out from notebook server

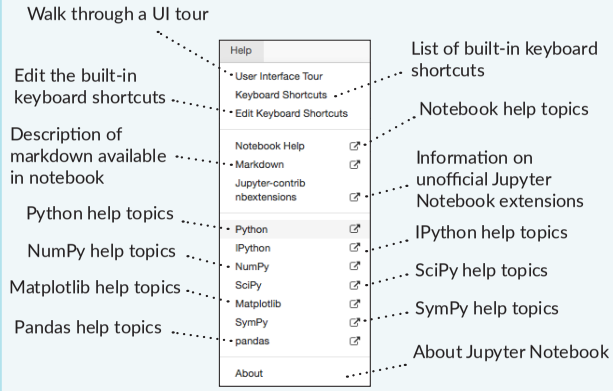
Executing Cells



View Cells



Asking For Help



Python for Data Science Cheat Sheet spaCy

Learn more Python for data science interactively at www.datacamp.com

DataCamp

About spaCy

spaCy is a free, open-source library for advanced Natural Language Processing (NLP) in Python. It's designed specifically for production use and helps you build applications that process and "understand" large volumes of text. **Documentation:** spacy.io

```
$ pip install spacy
```

```
import spacy
```

Statistical models

Download statistical models

Predict part-of-speech tags, dependency labels, named entities and more. See here for available models: spacy.io/models

```
$ python -m spacy download en_core_web_sm
```

Check that your installed models are up to date

```
$ python -m spacy validate
```

Loading statistical models

```
import spacy
# Load the installed model "en_core_web_sm"
nlp = spacy.load("en_core_web_sm")
```

Documents and tokens

Processing text

Processing text with the `nlp` object returns a `Doc` object that holds all information about the tokens, their linguistic features and their relationships

```
doc = nlp("This is a text")
```

Accessing token attributes

```
doc = nlp("This is a text")
# Token texts
[token.text for token in doc]
# ['This', 'is', 'a', 'text']
```

Spans

Accessing spans

Span indices are **exclusive**. So `doc[2:4]` is a span starting at token 2, up to – but not including! – token 4.

```
doc = nlp("This is a text")
span = doc[2:4]
span.text
# 'a text'
```

Creating a span manually

```
# Import the Span object
from spacy.tokens import Span
# Create a Doc object
doc = nlp("I live in New York")
# Span for "New York" with label GPE (geopolitical)
span = Span(doc, 3, 5, label="GPE")
span.text
# 'New York'
```

Linguistic features

Attributes return label IDs. For string labels, use the attributes with an underscore. For example, `token.pos_` .

Part-of-speech tags

PREDICTED BY STATISTICAL MODEL

```
doc = nlp("This is a text.")
# Coarse-grained part-of-speech tags
[token.pos_ for token in doc]
# ['DET', 'VERB', 'DET', 'NOUN', 'PUNCT']
# Fine-grained part-of-speech tags
[token.tag_ for token in doc]
# ['DT', 'VBZ', 'DT', 'NN', '.']
```

Syntactic dependencies

PREDICTED BY STATISTICAL MODEL

```
doc = nlp("This is a text.")
# Dependency labels
[token.dep_ for token in doc]
# ['nsubj', 'ROOT', 'det', 'attr', 'punct']
# Syntactic head token (governor)
[token.head.text for token in doc]
# ['is', 'is', 'text', 'is', 'is']
```

Named entities

PREDICTED BY STATISTICAL MODEL

```
doc = nlp("Larry Page founded Google")
# Text and label of named entity span
[(ent.text, ent.label_) for ent in doc.ents]
# [('Larry Page', 'PERSON'), ('Google', 'ORG')]
```

Syntax iterators

Sentences

USUALLY NEEDS THE DEPENDENCY PARSER

```
doc = nlp("This a sentence. This is another one.")
# doc.sents is a generator that yields sentence spans
[sent.text for sent in doc.sents]
# ['This is a sentence.', 'This is another one.']
```

Base noun phrases

NEEDS THE TAGGER AND PARSER

```
doc = nlp("I have a red car")
# doc.noun_chunks is a generator that yields spans
[chunk.text for chunk in doc.noun_chunks]
# ['I', 'a red car']
```

Label explanations

```
spacy.explain("RB")
# 'adverb'
spacy.explain("GPE")
# 'Countries, cities, states'
```

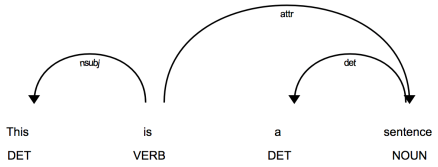
Visualizing

If you're in a Jupyter notebook, use `displacy.render` . Otherwise, use `displacy.serve` to start a web server and show the visualization in your browser.

```
from spacy import displacy
```

Visualize dependencies

```
doc = nlp("This is a sentence")
displacy.render(doc, style="dep")
```



Visualize named entities

```
doc = nlp("Larry Page founded Google")
displacy.render(doc, style="ent")
```

Larry Page PERSON founded Google ORG

Word vectors and similarity

To use word vectors, you need to install the larger models ending in `md` or `lg`, for example `en_core_web_lg`.

Comparing similarity

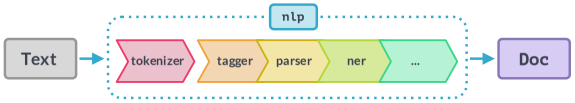
```
doc1 = nlp("I like cats")
doc2 = nlp("I like dogs")
# Compare 2 documents
doc1.similarity(doc2)
# Compare 2 tokens
doc1[2].similarity(doc2[2])
# Compare tokens and spans
doc1[0].similarity(doc2[1:3])
```

Accessing word vectors

```
# Vector as a numpy array
doc = nlp("I like cats")
# The L2 norm of the token's vector
doc[2].vector
doc[2].vector_norm
```

Pipeline components

Functions that take a `Doc` object, modify it and return it.



Pipeline information

```
nlp = spacy.load("en_core_web_sm")
nlp.pipe_names
# ['tagger', 'parser', 'ner']
nlp.pipeline
# [('tagger', <spacy.pipeline.Tagger>),
#  ('parser', <spacy.pipeline.DependencyParser>),
#  ('ner', <spacy.pipeline.EntityRecognizer>)]
```

Custom components

```
# Function that modifies the doc and returns it
def custom_component(doc):
    print("Do something to the doc here!")
    return doc

# Add the component first in the pipeline
nlp.add_pipe(custom_component, first=True)
```

Components can be added `first`, `last` (default), or `before` or `after` an existing component.

Extension attributes

Custom attributes that are registered on the global `Doc`, `Token` and `Span` classes and become available as `._`.

```
from spacy.tokens import Doc, Token, Span
doc = nlp("The sky over New York is blue")
```

Attribute extensions — WITH DEFAULT VALUE

```
# Register custom attribute on Token class
Token.set_extension("is_color", default=False)
# Overwrite extension attribute with default value
doc[6]._.is_color = True
```

Property extensions — WITH GETTER & SETTER

```
# Register custom attribute on Doc class
get_reversed = lambda doc: doc.text[::-1]
Doc.set_extension("reversed", getter=get_reversed)
# Compute value of extension attribute with getter
doc._.reversed
# 'eulb si kroY weN revo yks ehT'
```

Method extensions — CALLABLE METHOD

```
# Register custom attribute on Span class
has_label = lambda span, label: span.label_ == label
Span.set_extension("has_label", method=has_label)
# Compute value of extension attribute with method
doc[3:5].has_label("GPE")
# True
```

Rule-based matching

Using the matcher

```
# Matcher is initialized with the shared vocab
from spacy.matcher import Matcher
# Each dict represents one token and its attributes
matcher = Matcher(nlp.vocab)
# Add with ID, optional callback and pattern(s)
pattern = [{"LOWER": "new"}, {"LOWER": "york"}]
matcher.add("CITIES", None, pattern)
# Match by calling the matcher on a Doc object
doc = nlp("I live in New York")
matches = matcher(doc)
# Matches are (match_id, start, end) tuples
for match_id, start, end in matches:
    # Get the matched span by slicing the Doc
    span = doc[start:end]
    print(span.text)
# 'New York'
```

Rule-based matching

Token patterns

```
# "love cats", "loving cats", "loved cats"
pattern1 = [{"LEMMA": "love"}, {"LOWER": "cats"}]
# "10 people", "twenty people"
pattern2 = [{"LIKE_NUM": True}, {"TEXT": "people"}]
# "book", "a cat", "the sea" (noun + optional article)
pattern3 = [{"POS": "DET", "OP": "?"}, {"POS": "NOUN"}]
```

Operators and quantifiers

Can be added to a token dict as the `"OP"` key.

`!`	Negate pattern and match **exactly 0 times**.
`?`	Make pattern optional and match **0 or 1 times**.
`+`	Require pattern to match **1 or more times**.
`*`	Allow pattern to match **0 or more times**.

Glossary

Tokenization	Segmenting text into words, punctuation etc.
Lemmatization	Assigning the base forms of words, for example: "was" → "be" or "rats" → "rat".
Sentence Boundary Detection	Finding and segmenting individual sentences.
Part-of-speech (POS) Tagging	Assigning word types to tokens like verb or noun.
Dependency Parsing	Assigning syntactic dependency labels, describing the relations between individual tokens, like subject or object.
Named Entity Recognition (NER)	Labeling named "real-world" objects, like persons, companies or locations.
Text Classification	Assigning categories or labels to a whole document, or parts of a document.
Statistical model	Process for making predictions based on examples.
Training	Updating a statistical model with new examples.

Git Cheat Sheet

Git Basics

`git init <directory>`	Create empty Git repo in specified directory. Run with no arguments to initialize the current directory as a git repository.
`git clone <repo>`	Clone repo located at `<repo>` onto local machine. Original repo can be located on the local filesystem or on a remote machine via `HTTP` or `SSH`.
`git config user.name <name>`	Define author name to be used for all commits in current repo. Devs commonly use `--global` flag to set config options for current user.
`git add <directory>`	Stage all changes in `<directory>` for the next commit. Replace `<directory>` with a `<file>` to change a specific file.
`git commit -m "<message>"`	Commit the staged snapshot, but instead of launching a text editor, use `<message>` as the commit message.
`git status`	List which files are staged, unstaged, and untracked.
`git log`	Display the entire commit history using the default format. For customization see additional options.
`git diff`	Show unstaged changes between your index and working directory.

Undoing Changes

`git revert <commit>`	Create new commit that undoes all of the changes made in `<commit>`, then apply it to the current branch.
`git reset <file>`	Remove `<file>` from the staging area, but leave the working directory unchanged. This unstages a file without overwriting any changes.
`git clean -n`	Shows which files would be removed from working directory. Use the `-f` flag in place of the `-n` flag to execute the clean.

Rewriting Git History

`git commit --amend`	Replace the last commit with the staged changes and last commit combined. Use with nothing staged to edit the last commit's message.
`git rebase <base>`	Rebase the current branch onto `<base>`. `<base>` can be a commit ID, a branch name, a tag, or a relative reference to `HEAD`.
`git reflog`	Show a log of changes to the local repository's `HEAD`. Add `--relative-date` flag to show date info or `--all` to show all refs.

Git Branches

`git branch`	List all of the branches in your repo. Add a `<branch>` argument to create a new branch with the name `<branch>`.
`git checkout -b <branch>`	Create and check out a new branch named `<branch>`. Drop the `-b` flag to checkout an existing branch.
`git merge <branch>`	Merge `<branch>` into the current branch.

Remote Repositories

`git remote add <name> <url>`	Create a new connection to a remote repo. After adding a remote, you can use `<name>` as a shortcut for `<url>` in other commands.
`git fetch <remote> <branch>`	Fetches a specific `<branch>`, from the repo. Leave off `<branch>` to fetch all remote refs.
`git pull <remote>`	Fetch the specified remote's copy of current branch and immediately merge it into the local copy.
`git push <remote> <branch>`	Push the branch to `<remote>`, along with necessary commits and objects. Creates named branch in the remote repo if it doesn't exist.

Additional Options +

git config

`git config --global user.name <name>`	Define the author name to be used for all commits by the current user.
`git config --global user.email <email>`	Define the author email to be used for all commits by the current user.
`git config --global alias. <alias-name> <git-command>`	Create shortcut for a Git command. E.g. `alias.glog log --graph --oneline` will set `git glog` equivalent to `git log --graph --oneline`.
`git config --system core.editor <editor>`	Set text editor used by commands for all users on the machine. `<editor>` arg should be the command that launches the desired editor (e.g., vi).
`git config --global --edit`	Open the global configuration file in a text editor for manual editing.

git log

`git log -<limit>`	Limit number of commits by `<limit>`. E.g. `git log -5` will limit to 5 commits.
`git log --oneline`	Condense each commit to a single line.
`git log -p`	Display the full diff of each commit.
`git log --stat`	Include which files were altered and the relative number of lines that were added or deleted from each of them.
`git log --author= "<pattern>"`	Search for commits by a particular author.
`git log --grep="<pattern>"`	Search for commits with a commit message that matches `<pattern>`.
`git log <since>..<until>`	Show commits that occur between `<since>` and `<until>`. Args can be a commit ID, branch name, `HEAD`, or any other kind of revision reference.
`git log -- <file>`	Only display commits that have the specified file.
`git log --graph --decorate`	`--graph` flag draws a text based graph of commits on left side of commit msgs. `--decorate` adds names of branches or tags of commits shown.

git diff

`git diff HEAD`	Show difference between working directory and last commit.
`git diff --cached`	Show difference between staged changes and last commit

git reset

`git reset`	Reset staging area to match most recent commit, but leave the working directory unchanged.
`git reset --hard`	Reset staging area and working directory to match most recent commit and **overwrites all changes** in the working directory.
`git reset <commit>`	Move the current branch tip backward to `<commit>`, reset the staging area to match, but leave the working directory alone.
`git reset --hard <commit>`	Same as previous, but resets both the staging area & working directory to match. **Deletes** uncommitted changes, and **all commits after** `<commit>`.

git rebase

`git rebase -i <base>`	Interactively rebase current branch onto `<base>`. Launches editor to enter commands for how each commit will be transferred to the new base.

git pull

`git pull --rebase <remote>`	Fetch the remote's copy of current branch and rebases it into the local copy. Uses git rebase instead of merge to integrate the branches.

git push

`git push <remote> --force`	Forces the `git push` even if it results in a non-fast-forward merge. Do not use the `--force` flag unless you're absolutely sure you know what you're doing.
`git push <remote> --all`	Push all of your local branches to the specified remote.
`git push <remote> --tags`	Tags aren't automatically pushed when you push a branch or use the `--all flag`. The `--tags` flag sends all of your local tags to the remote repo.