Cloud Computing and Big Data

Machine Learning

Oxford University
Software Engineering Programme
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- The overall process
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Definition of Machine Learning

- Algorithms that can learn from data

Definition of Machine Learning

- Algorithms that can learn from data

Ok that was a circular definition ☺

Definition take 2

- Algorithms that can analyse a set of data to find patterns and then make predictions when new data comes in

Uses of Machine Learning

- Fraud Detection
  - Spam emails, fake reviews, credit card fraud
- Personalization
  - Recommendations
- Targeted Marketing
  - Predictive preferences, cross-selling
- Content Classification
  - Document classification, sentiment analysis
- Customer Support
  - Social media analysis
- Many others

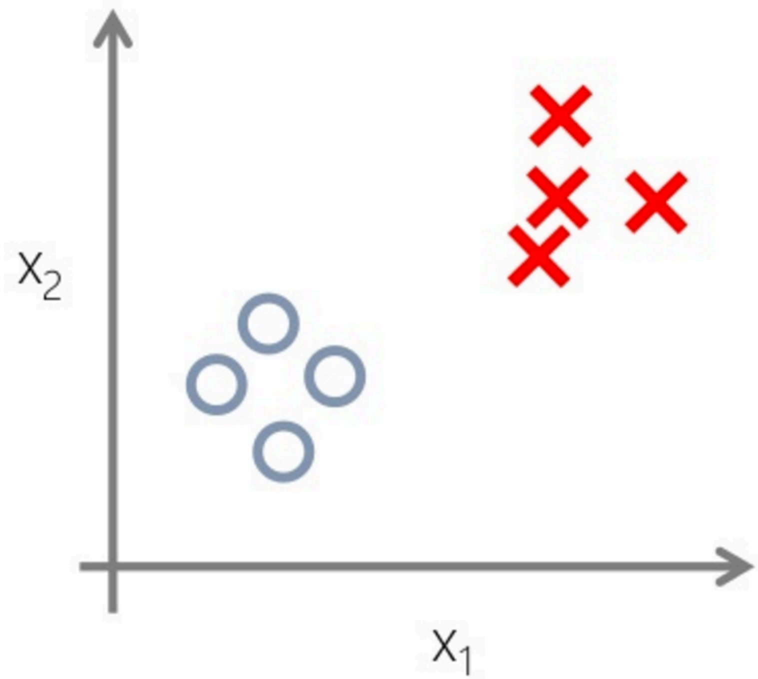
Learning phase

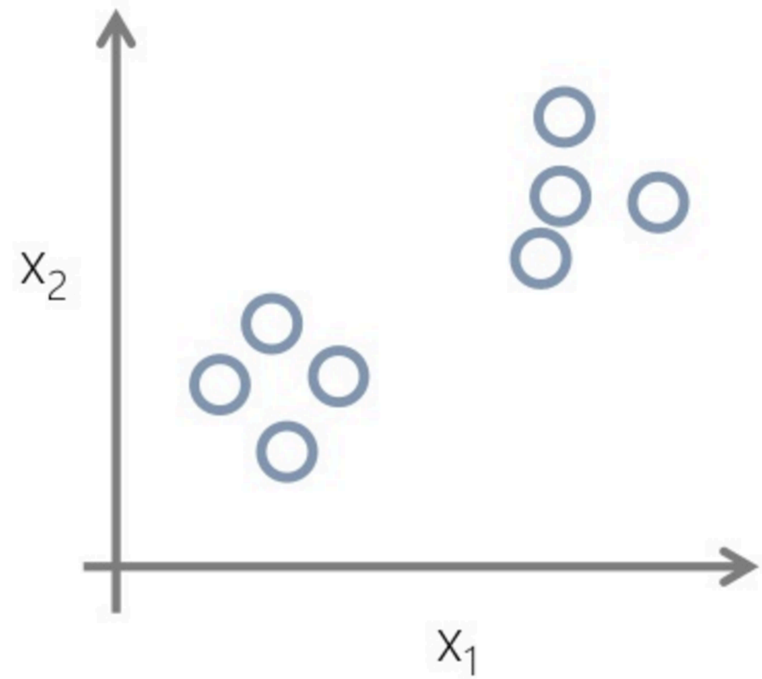
Usage phase

Terminology

- Sample
  - Some incoming data to be analysed
  - E.g. a JPG picture
- Feature
  - Some quantifiable data from the sample
  - E.g. colour, height, width, pixel data, etc
- Label
  - Some useful information about the sample that we wish to categorise:
    - E.g. looking at a picture this is a person
- Model
  - The output of some learning algorithm
  - The parameterization of an algorithm that can be run against new data

Supervised vs Unsupervised





Source: http://www.slideshare.net/damirdobric

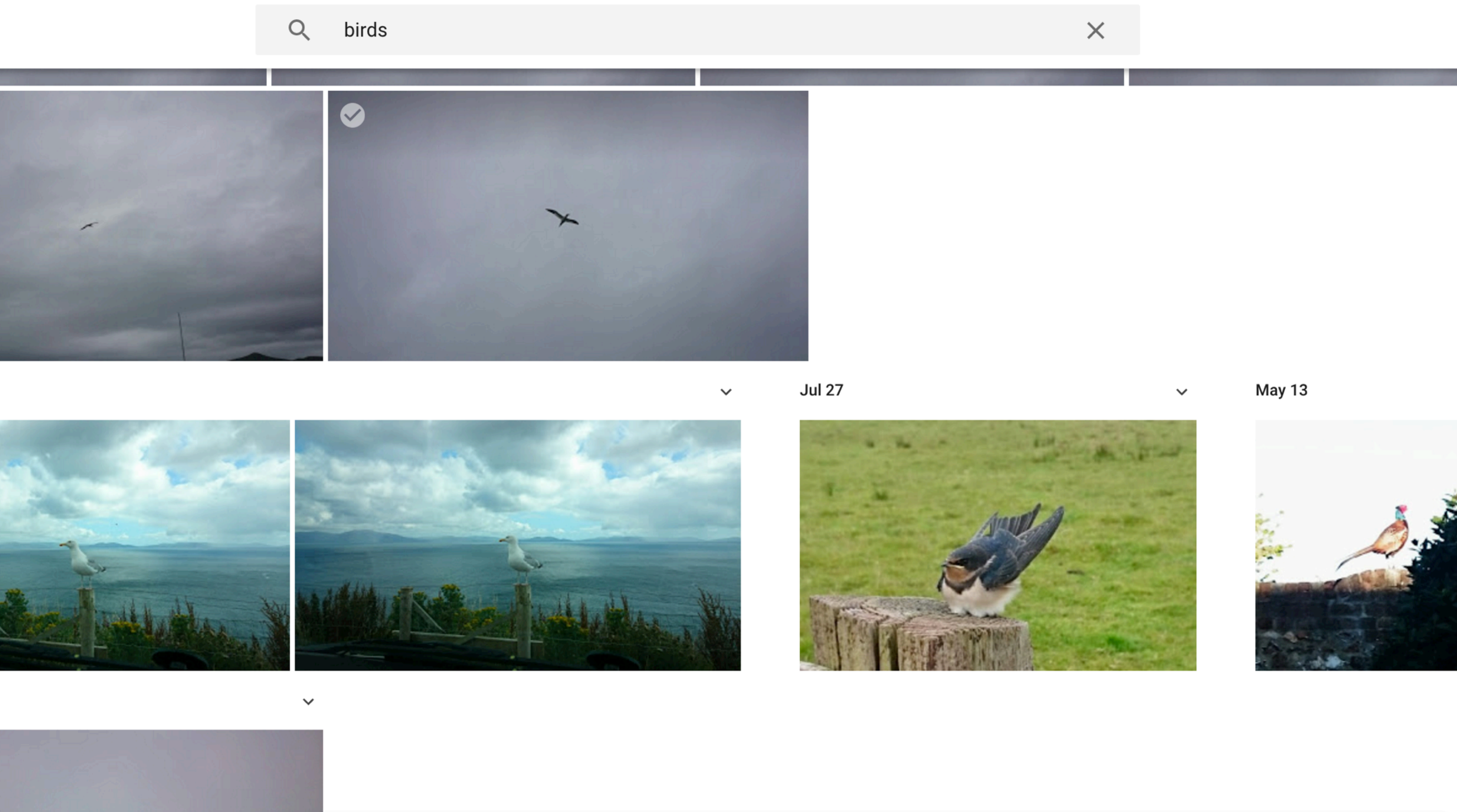
Types of learning

- Supervised
  - The required labels are known
  - Aiming to find an algorithm that correctly identifies these
  - Iterative exploration and refinement
  - Useful for prediction
- Unsupervised
  - The labels are not known
  - The system identifies new classifications
  - Exploring the past, better understanding it

Types of machine learning

- Classification
- Regression / Prediction
- Clustering
- Recommendation and Collaborative Filtering
- Frequent Pattern mining

Classification

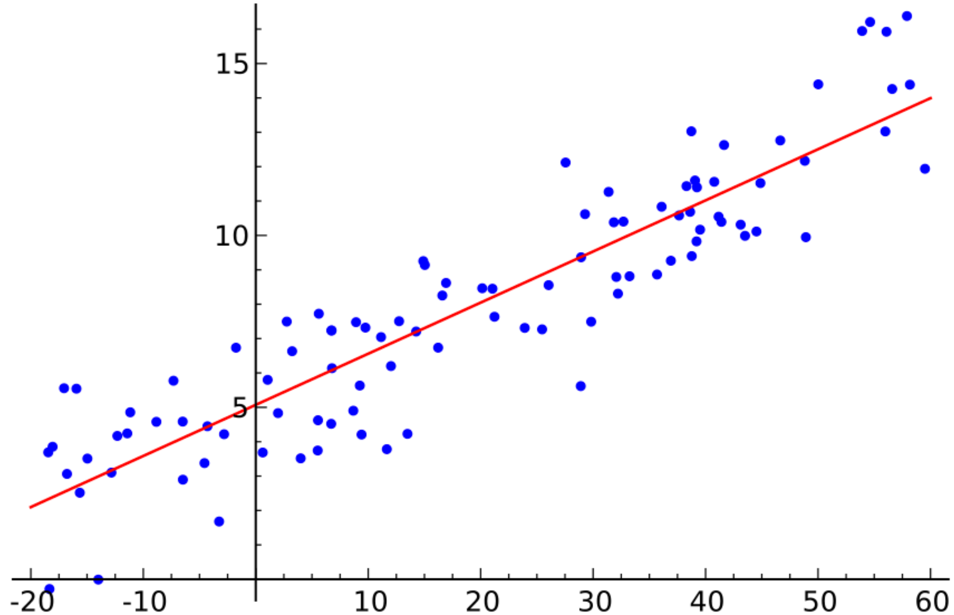


Classification

- Identifying a class into which this sample fits
  - E.g. look at a picture and decide if it contains a bird
  - A key part of artificial intelligence
  - Also deeply useful for making sense of big data

Regression

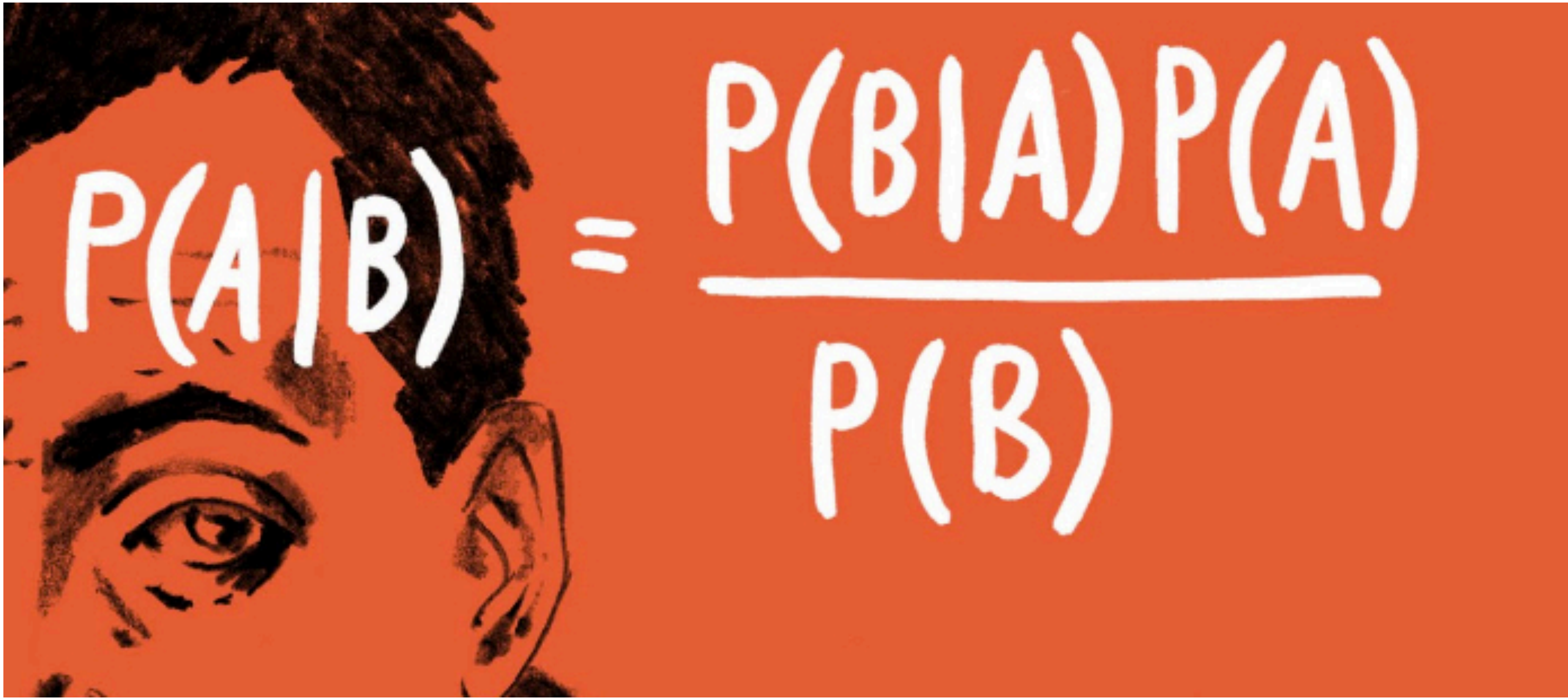
- Applying a model based on previous data
  - Allows prediction of future state
- Many statistical techniques



Regression vs Classification

- Regression produces a real number or numbers
  - i.e. a continuously varying answer or answers
- Classification identifies a set or element of a set
  - E.g. False, Blue, Person, High-Value Customer

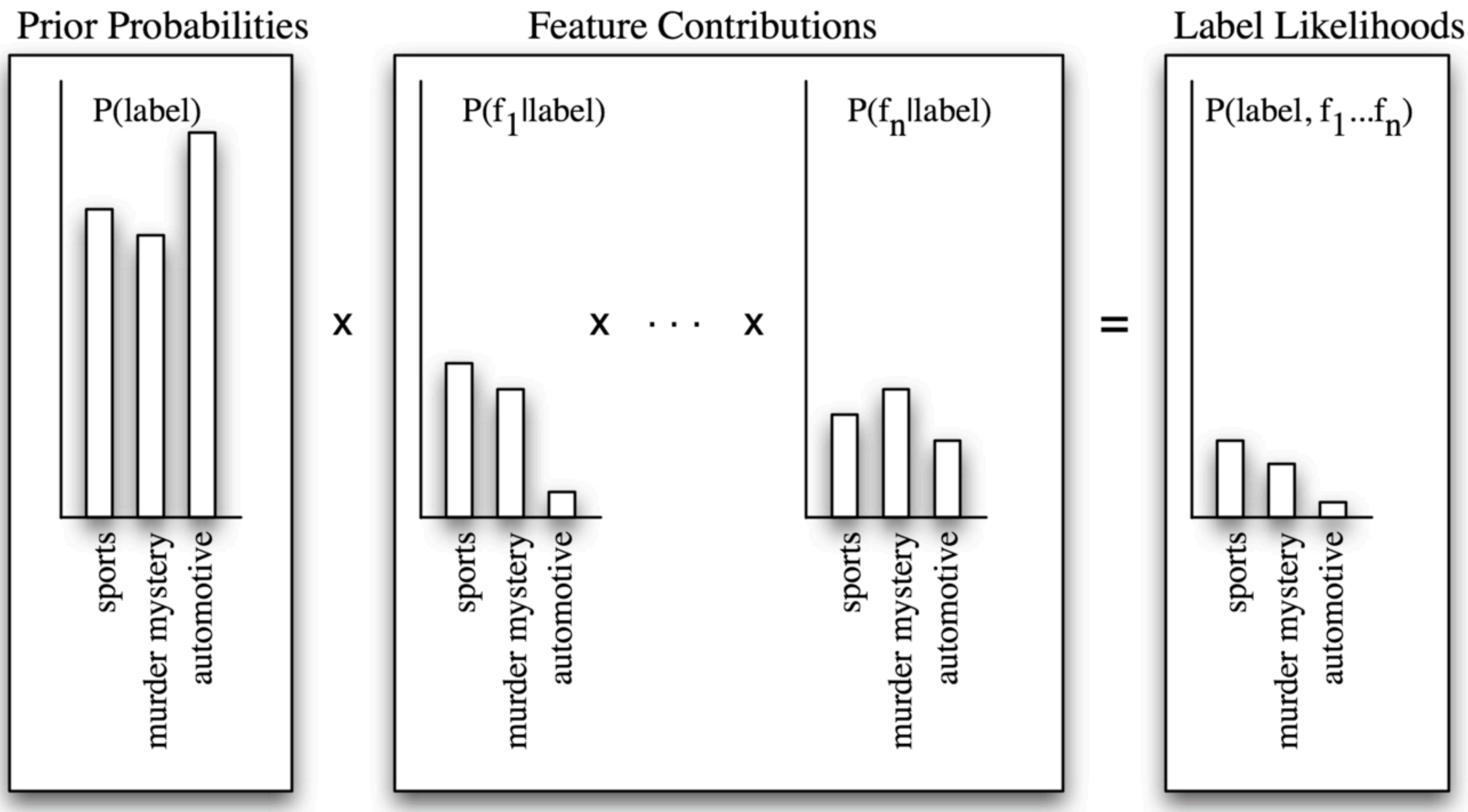
Bayes Theorem



P(A|B) is the probability of A given B
P(A) is the probability of A without regard to B

Classification Algorithms

Naïve Bayes



Spark MLLib's algorithms

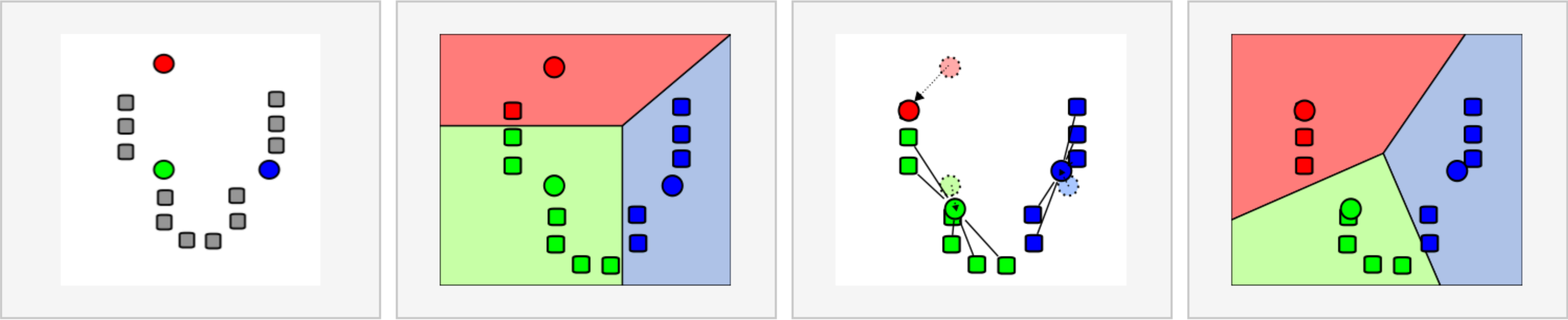
Problem Type	Supported Methods
Binary Classification	linear SVMs, logistic regression, decision trees, random forests, gradient-boosted trees, naive Bayes
Multiclass Classification	decision trees, random forests, naive Bayes
Regression	linear least squares, Lasso, ridge regression, decision trees, random forests, gradient-boosted trees, isotonic regression

Clustering

- Grouping items into clusters
  - Where items in a cluster are more similar to each other than to items in other clusters
- Basically creating the classifications from the data rather than applying them a priori

K-Means Clustering

Demonstration of the standard algorithm



1. *k* initial "means" (in this case *k*=3) are randomly generated within the data domain (shown in color).

2. *k* clusters are created by associating every observation with the nearest mean. The partitions here represent the Voronoi diagram generated by the means.

3. The centroid of each of the *k* clusters becomes the new mean.

4. Steps 2 and 3 are repeated until convergence has been reached.

MLLib's clustering

- K-means
- Gaussian mixture
- Power iteration clustering (PIC)
- Latent Dirichlet allocation (LDA)
- Streaming k-means

Recommendation and Collaborative Filtering

- Given a user's interaction with items, what else are they likely to prefer

Large-scale Parallel Collaborative Filtering for the Netflix Prize

Yunhong Zhou, Dennis Wilkinson, Robert Schreiber and Rong Pan

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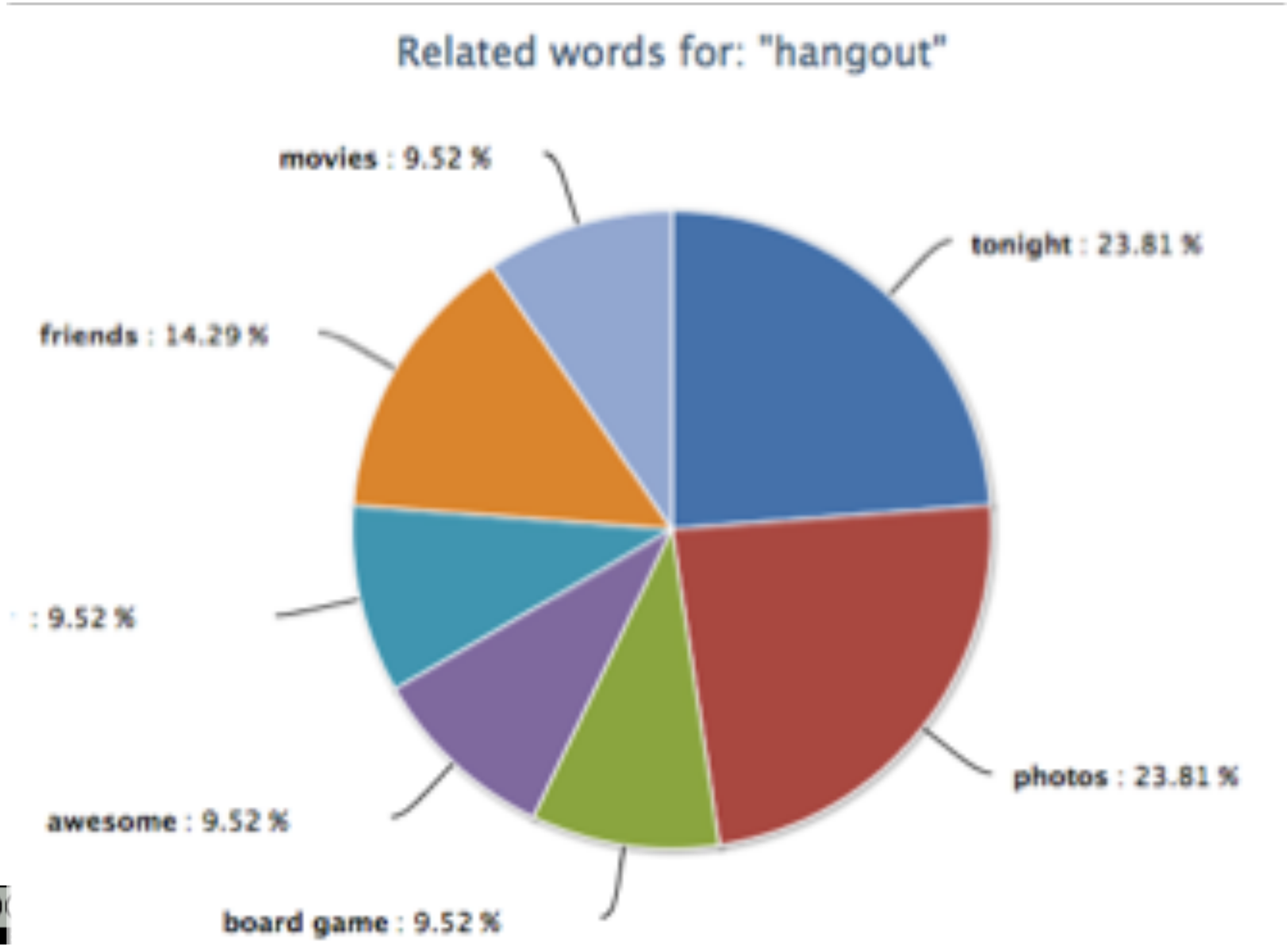
Abstract. Many recommendation systems suggest items to users by utilizing the techniques of collaborative filtering (CF) based on historical records of items that the users have viewed, purchased, or rated. Two major problems that most CF approaches have to resolve are scalability and sparseness of the user profiles. In this paper, we describe *Alternating-Least-Squares with Weighted-λ-Regularization* (ALS-WR), a parallel algorithm that we designed for the Netflix Prize, a large-scale collaborative filtering challenge. We use parallel Matlab on a Linux cluster

Frequent Pattern Mining

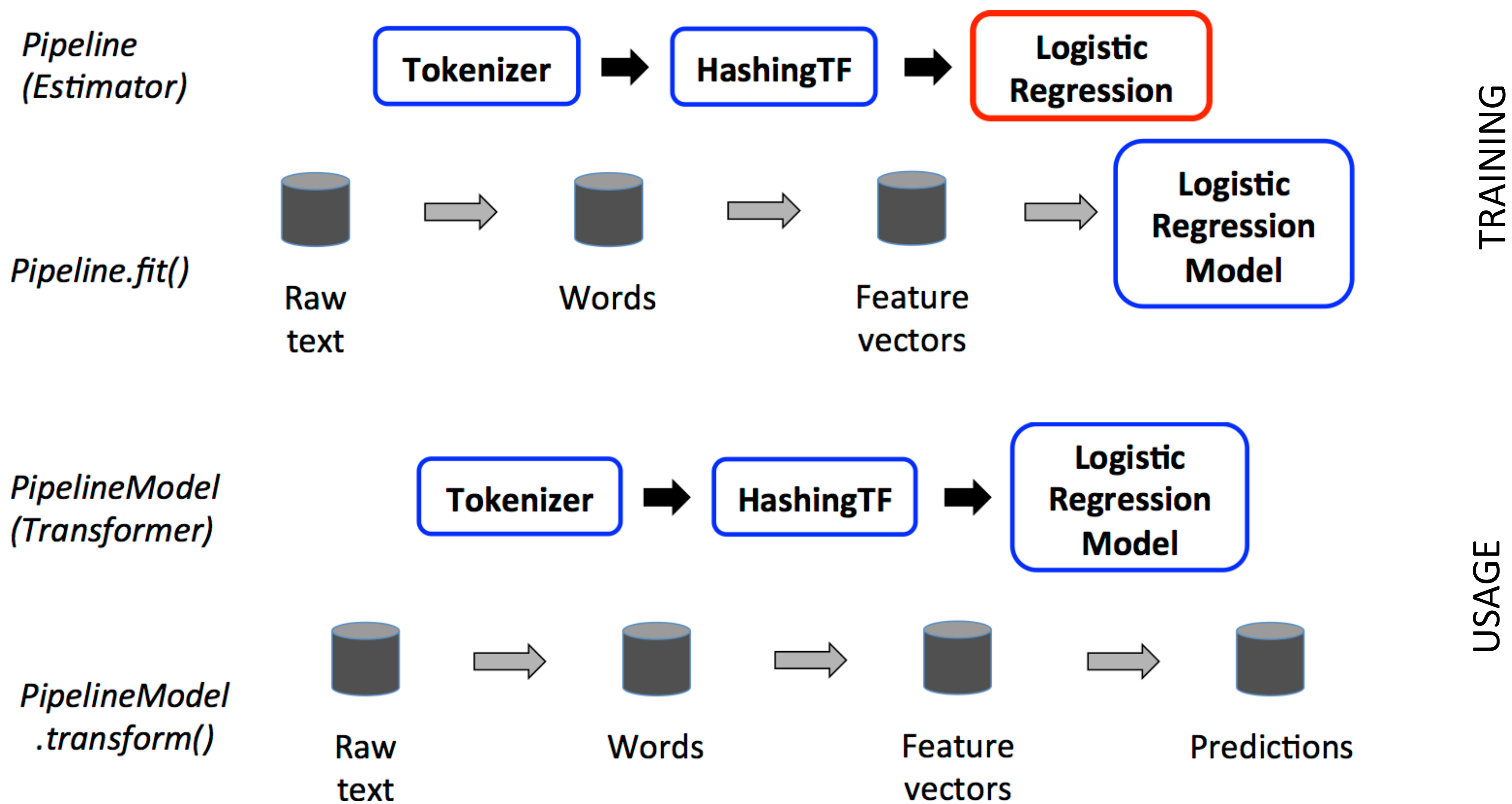
Related topics: @cassiomelo Your last post was about a hangout. These are the topics you relate to hangout: tonight, movies, board game, friends, awesome, photos, bar and NBA.



MLLib FPM

- Frequent pattern mining
  - FP-growth
  - association rules
  - PrefixSpan

Spark MLLib Pipelines



Big Data ML

- Obviously we can learn more insights with more data
- Many examples
  - Netflix competition
  - Google, Facebook, Twitter etc are all doing big data ML
- Obviously we want the right algorithms:
  - E.g. Kmeans++ is a parallelizable version of Kmeans
- MLLib and Mahout come pre-built with these

Amazon Machine Learning

Powerful machine learning technology

Based on Amazon's battle-hardened internal systems

Not just the algorithms:
- Smart data transformations
- Input data and model quality alerts
- Built-in industry best practices

Grows with your needs
- Train on up to 100 GB of data
- Generate billions of predictions
- Obtain predictions in batches or real-time

Predictive Model Markup Language (PMML)

- An XML language for sharing models from machine learning
- Supported by R and other packages
- Mahout has no support
- Spark can export but not yet import
  - Scala only so far

Google Tensor Flow

TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems

(Preliminary White Paper, November 9, 2015)

Martín Abadi, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S. Corrado, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Ian Goodfellow, Andrew Harp, Geoffrey Irving, Michael Isard, Yangqing Jia, Rafal Jozefowicz, Lukasz Kaiser, Manjunath Kudlur, Josh Levenberg, Dan Mané, Rajat Monga, Sherry Moore, Derek Murray, Chris Olah, Mike Schuster, Jonathon Shlens, Benoit Steiner, Ilya Sutskever, Kunal Talwar, Paul Tucker, Vincent Vanhoucke, Vijay Vasudevan, Fernanda Viégas, Oriol Vinyals, Pete Warden, Martin Wattenberg, Martin Wicke, Yuan Yu, and Xiaoqiang Zheng

Google Research*

Abstract

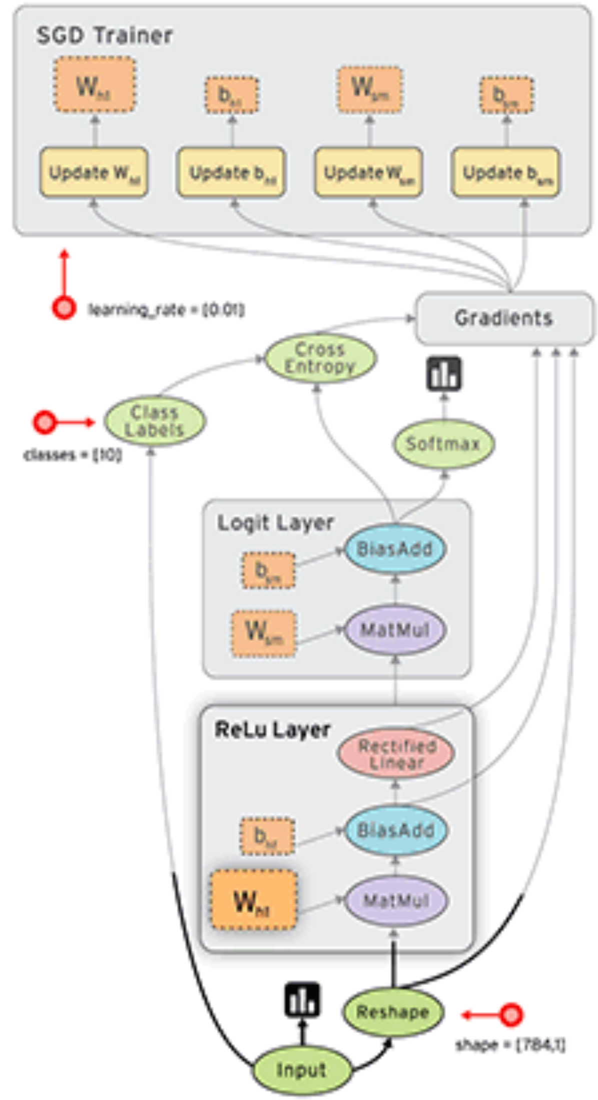
TensorFlow [1] is an interface for expressing machine learning algorithms, and an implementation for executing such algorithms. A computation expressed using TensorFlow can be executed with little or no change on a wide variety of heterogeneous systems, ranging from mobile devices such as phones and tablets up to large-scale distributed systems of hundreds of machines and thousands of computational devices such as GPU cards. The system is flexible and can be used to express a wide variety of algorithms, including training and inference algorithms for deep neural network models, and it has been used for conducting research and for deploying machine learning systems into production across more than a dozen areas of computer science and other fields, including speech recognition, computer vision, robotics, information retrieval, natural language processing, geographic information extraction, and computational drug discovery. This paper describes the TensorFlow interface and an implementation of that interface that we have built at Google. The TensorFlow API and a reference implementation were released as an open-source package under

sequence prediction [47], move selection for Go [34], pedestrian detection [2], reinforcement learning [38], and other areas [17, 5]. In addition, often in close collaboration with the Google Brain team, more than 50 teams at Google and other Alphabet companies have deployed deep neural networks using DistBelief in a wide variety of products, including Google Search [11], our advertising products, our speech recognition systems [50, 6, 46], Google Photos [43], Google Maps and StreetView [19], Google Translate [18], YouTube, and many others.

Based on our experience with DistBelief and a more complete understanding of the desirable system properties and requirements for training and using neural networks, we have built TensorFlow, our second-generation system for the implementation and deployment of large-scale machine learning models. TensorFlow takes computations described using a dataflow-like model and maps them onto a wide variety of different hardware platforms, ranging from running inference on mobile device platforms such as Android and iOS to modest-

TensorFlow

- Recently (Nov 2015) announced and open sourced
- CPU and GPU support with no coding changes
- Neural networks plus arbitrary dataflows
- www.tensorflow.org



Recap

- Machine Learning is a powerful way of gaining insight and value from big data
  – Recommendation
  – Classification and prediction
  – Clustering and understanding
- Many coding and deployment options
- Built into Spark, Hadoop and AWS

Questions?