Large Scale Distributed Machine Learning on Apache Spark

SSG, Big Data Technology

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Fraud Detection on Apache Spark

- Goal:
  - Given card transaction details, classify whether the transaction is fraud or normal.
- Data overview:
  - Billions of transaction records. (unbalanced)
  - Hundreds of raw features for each record (flag, categorical and numeric features).
  - Training dataset
  - Test Dataset
- Evaluation Matrices
  - Recall = predicted fraud / all real fraud transaction.
  - Precision = predicted fraud correctly / predicted fraud

Fraud can mean:

Buying with stolen credit cards

Abusing promotional programs

Account takeover

Spamming other users

Feature Engineering 1. understanding Data

- Statistical analysis for the raw features
  - categorical features => Distinct, group by count, etc.
  - for numeric features => Min, max, avg, variance, etc.
  - feature distribution
- Feature Generation
  - We need to derive more logical features
  - Reflect location change, abnormal amount, high risk region…
- Data verification and cleaning

Model Training 1. choosing algorithm

- Algorithm comparison:
  - Neural network vs. GBDT(Gradient Boosting Decision Tree)

- Bootstrap aggregating (bagging)
  - Single model reaches limit after certain rounds of tuning.
  - Reduce problems related to over-fitting
  - Allow better performance and flexibility during training

Some experiences and next step

- Experience:
  - Speed up the feedback cycle: The key in model tuning is to shorter the feedback cycle between training and evaluation. Automate the process wherever possible, by leveraging the pipeline, model persistence and grid search system.
  - Transform features according to its properties: Features should be carefully evaluated. Categorical features need to be handled differently according to their distribution and number of distinct values.
  - Automatic feature selection can be too expensive. Leverage Information value to narrow down the scope.

Topic Modeling

- Automatically infers the topics discussed in a collection of documents.
- These topics can be used to summarize and organize documents, or used for featurization and dimensionality reduction
  - What is document X discussing?
  - How similar are documents X and Y?
  - If I am interested in topic Z, which documents should I read first?
- Widely applied
  - Document, image clustering
  - feature deduction
  - Social network, advertising …

Intuition of LDA

Corpus

doc1. apple banana

doc2. apple orange

doc3. banana orange

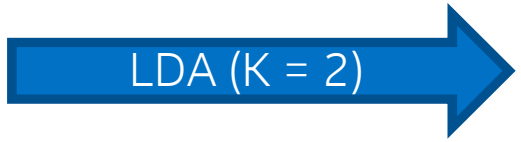
doc4. tiger cat

doc5. tiger dog

doc6. cat dog

doc7. Cat dog apple

Input (what we have)



	Topic 1	Topic2
Apple	33%	0%
Banana	33%	0%
Orange	33%	0%
Tiger	0%	33%
Cat	0%	33%
Dog	0%	33%

	Topic 1	Topic2
doc1	100%	0%
doc2	100%	0%
doc3	100%	0%
doc4	0%	100%
doc5	0%	100%
doc6	0%	100%
doc7	33%	66%

Output (what we want)

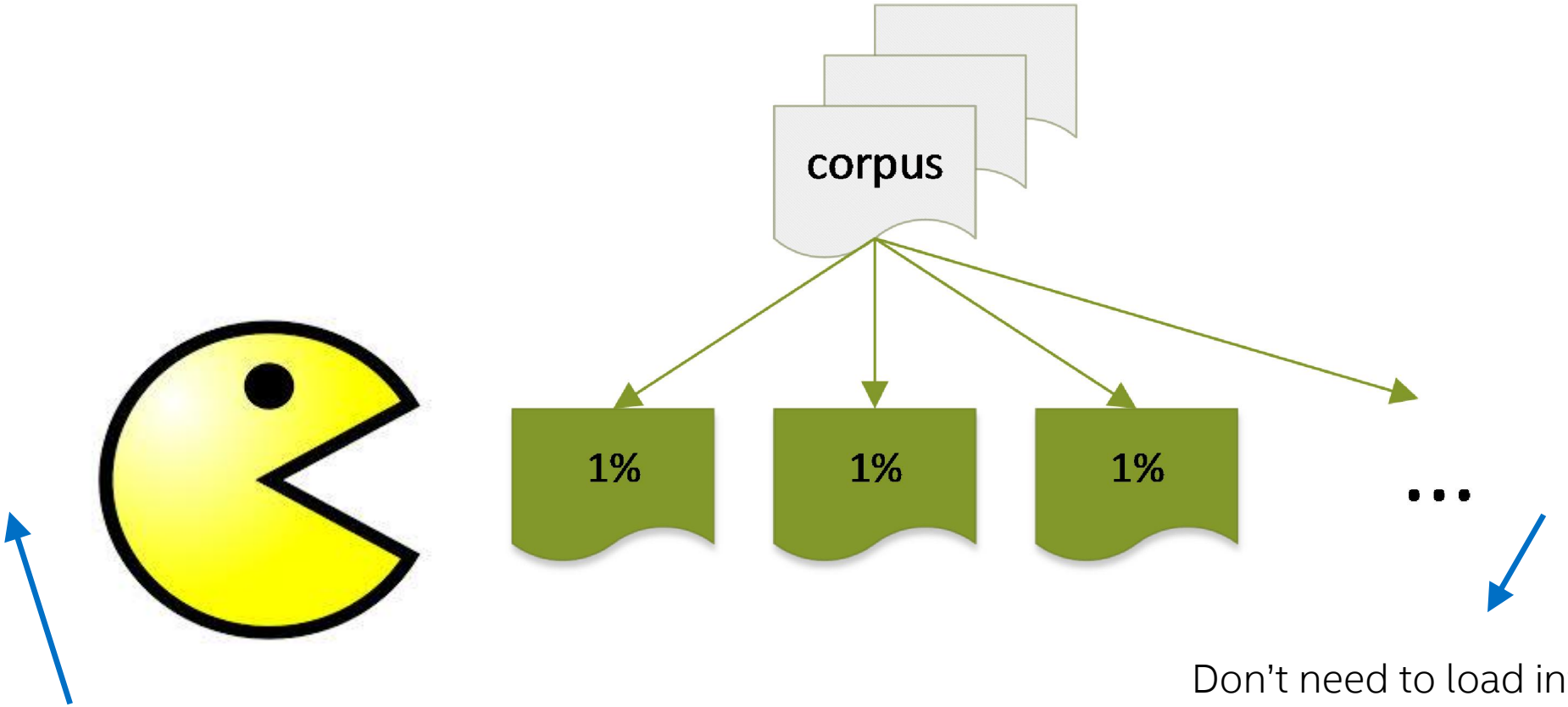
Existing Solution

- Variational EM (Expectation-maximization)
  - Numerical approximation using lower-bounds
  - Results in biased solutions
  - Convergence has numerical guarantees
- Gibss Sampling
  - Stochastic simulation
  - unbiased solutions
  - Stochastic convergence

OOM~

Both needs to load the entire corpus into memory and scan through the corpus in each iteration !!!

Make it online



Can be discarded after processing

Don’t need to load into memory in advance

Online LDA

Algorithm 2 Online variational Bayes for LDA

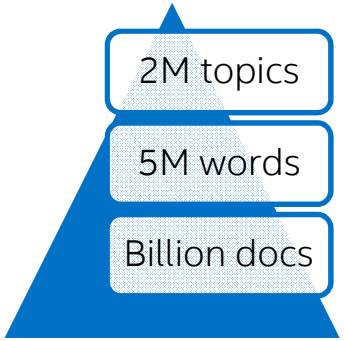
Define $\rho_t \triangleq (\tau_0 + t)^{-\kappa}$
Initialize $\boldsymbol{\lambda}$ randomly.
for $t = 0$ to ∞ **do**
  E step:
  Initialize $\gamma_{tk} = 1$. (The constant 1 is arbitrary.)
  repeat
    Set $\phi_{twk} \propto \exp\{\mathbb{E}_q[\log \theta_{tk}] + \mathbb{E}_q[\log \beta_{kw}]\}$
    Set $\gamma_{tk} = \alpha + \sum_w \phi_{twk} n_{tw}$
  until $\frac{1}{K} \sum_k |\text{change in} \gamma_{tk}| < 0.00001$
  M step:
  Compute $\tilde{\lambda}_{kw} = \eta + D n_{tw} \phi_{twk}$
  Set $\boldsymbol{\lambda} = (1 - \rho_t)\boldsymbol{\lambda} + \rho_t \tilde{\boldsymbol{\lambda}}$.
end for

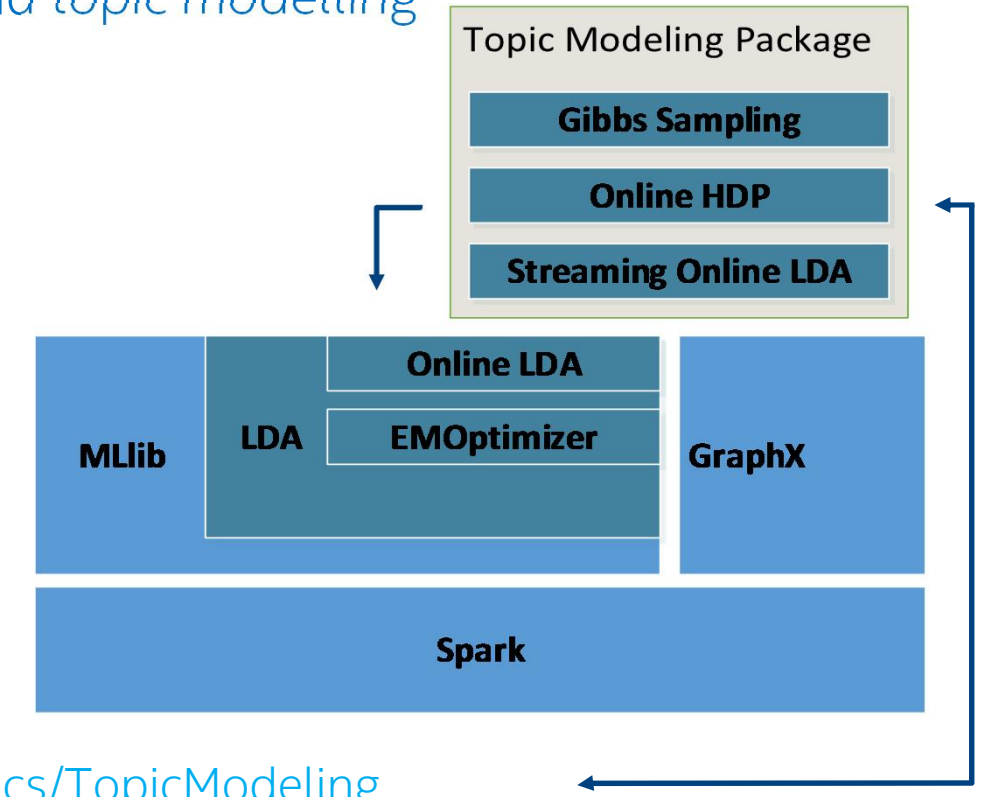
$$\rho_t \triangleq (\tau_0 + t)^{-\kappa}$$

Large-Scale Topic Modeling on Spark

- Adopted by many top Internet companies for text mining and topic modelling

Clustering	• Images • News, advertisements
Feature reduction	• Documents to Topics
Analysis	• Auto Tagging, • Emotional Analysis





- Full function coverage
  - Large batch computation or online model
  - Training, Prediction, Analysis.
- Spark Package: Topic Modeling https://github.com/intel-analytics/TopicModeling
  - Under active development, welcome to join.
  - Intel is one of the primary contributors for LDA algorithms in Spark MLlib.

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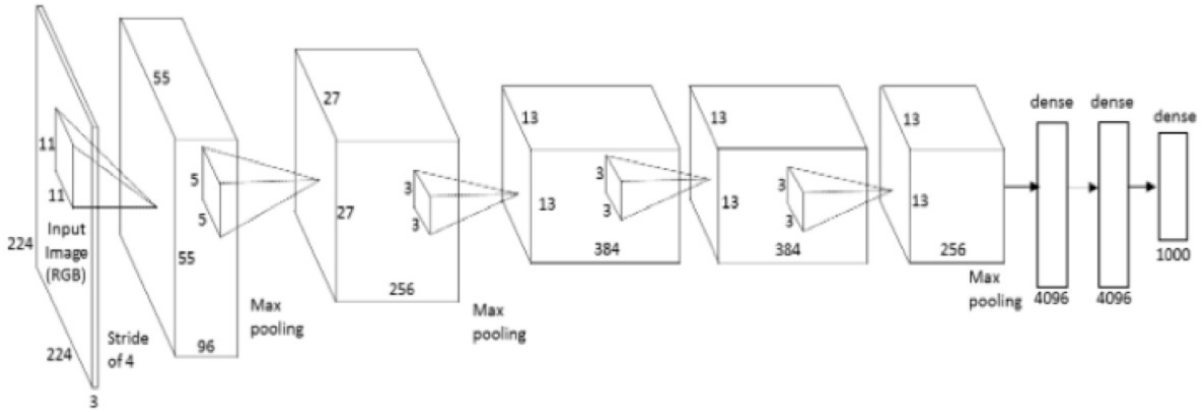
Deep (Convolutional) neural network

Intuitive API with layer-based interface




```
val trainData = loadData()
val model = new Sequential(…)
model += new Convolution(…)
model += new maxPooling(…)
…
val criterion = new ClassNLLCriterion()
val optimizer = new ParallelOptimizer (model, new SGD)
optimizer.setCrossValidation(evaluator.accuracy)
optimizer.setPath("./model_save.obj")
optimizer.optimize(trainData)
```

Built on top of standard Big Data platforms

- Easily utilize your existing clusters

Engaging industry users and community early

- Evolving with feedback from practical cases
- Community version compatible with Spark MLP.

Targeting Full function coverage:

- Auto Encoder, Sparse Encoder
- Convolution with max and avg pooling
- RBM and DBN

Benchmark with popular dataset / models

- Mnist
- AlexNet
- cifar 10

Easy MKL integration for IA acceleration

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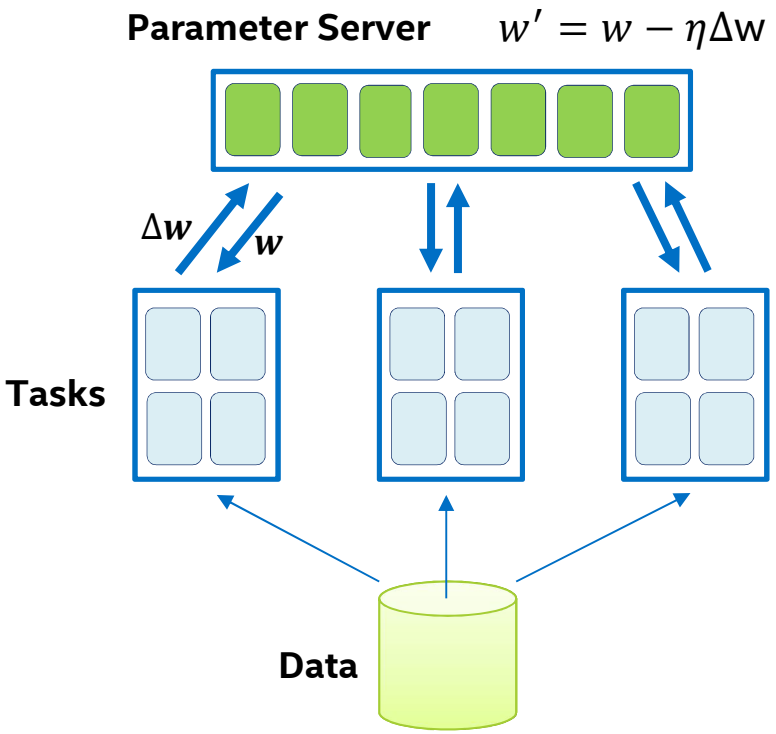
Parameter Support for Distributed Machine Learning



Successful support for algorithms with linear algebra

- Gradient and weight in logistic regression
- Word-topic distribution/assignment in LDA
- Weight & bias in neural network
- More algorithms are under development and welcome to join.

Scale-out framework to support complex model & training

- Very large scale model/graph (billions of unique features)
- Asynchronous model for distributed training
- Parallel aggregation & update of parameters
- Coarse-grained fault tolerance scheme

Going Spark
Initial proposal/discussions in Spark-10041
Definition of the proper PS interface in Spark, Linear algebra objects, partitioning strategies, epoch support, parallel aggregation, etc.

Machine learning algorithms and Statistics

Need more statistics in Spark? We have a package

- https://github.com/intel-analytics/StatisticsOnSpark
- ANOVA, T sampling, Mann–Whitney U test and more.

Word2Vec Improvements

- Fundamental NLP algorithms, for similarity computation or preprocessing.
- Greatly enlarged the maximum dictionary size
- Reduce memory consumption and execution time.

KMeans support for sparse data:

- Clustering with web scale: Billions of records with dimension of 10M, 200 clusters
- Greatly reduce memory consumption for sparse data.

- Need support for other algorithms? Talk to us, we probably have done that !

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