CS535 BIG DATA

PART 1. BATCH COMPUTING MODELS FOR BIG DATA ANALYTICS

2. LARGE SCALE DATA ANALYSIS USING SPARK WITH CASE STUDY

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FAQs

- PA1 demo is going on
- Term Project
  - 10/7 5:00PM
  - Description available on the course web
  - Presentation schedule
  - Google computing cluster credit is available

Proposal

- Title of your project
- Problem formulation
- Your strategy to solve the problem
- Functions targeted by your software
- Plan for testing
- Evaluation method
- Project timeline (weekly plan)
- Bibliography
- Submission (1,200-1,800 words)

Presentations (10/11, and 10/13)

- Slide 1: Title (with the team info)
- Slide 2: Problem statement
- Slide 3: Your approach
- Slide 4: Your software
- Slide 5: Plan for software testing
- Slide 6: Evaluation Method

- Presentation should be no longer than **12 minutes** including the Q&A session. (10 minutes: presentation, 2 minutes: Q&A)
- All of the team members should present
- Audience will get 2% of participation score based on their questions and attendance
- Please send me your slides **at least 2 hours** before your presentation

Objectives

- Recommendation systems
  - Collaborative filtering
  - Latent factor approach
- Linear Methods

Large scale data analysis using Spark

CASE STUDY: Recommending Music and the Audioscrobbler Dataset

Evaluating the Recommendation Model

What is a "**good**" recommendation?

- "a popular artist"?
- "artists the user has listened to"?
- "artists the user will listen to"?

Preparing data for evaluation

- To perform a meaningful evaluation, some of the artist play data can be set aside
  - Hidden from the ALS model building process
- The held-out data can be used as a collection of good recommendations for each user
- Compute the recommender's score

For building model	For testing model

AUC metric

- Rank 1.0 is perfect, 0.0 is the worst
- Receiver Operating Characteristic (ROC)
  - Based on the rank used to decide final recommendations
- Area Under the Curve (AUC) of ROC may be used as the probability that a randomly chosen good recommendation ranks above a randomly chosen bad recommendation
- Spark's `BinaryCalssficationMetrics`
  - Computes AUC per users and averages the result
  - Generating mean AUC

MAP metric

- Mean average precision
  - Focuses on the top recommendations

Computing AUC

- 90% of the data is used for training and the remaining 10% for validation

```
import org.apache.spark.rdd._

def areaUnderCurve(
    positiveData: RDD[ Rating],
    bAllItemIDs: Broadcast[ Array[ Int]],
    predictFunction: (RDD[( Int, Int)] = >
RDD[Rating])) = {
...
}

val allData = buildRatings( rawUserArtistData, bArtistAlias)
val Array( trainData, cvData) =
allData.randomSplit(Array( 0.9, 0.1))
```

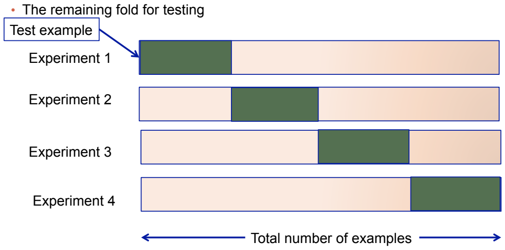

Computing AUC

- continued

```
trainData.cache()
cvData.cache()

val allItemIDs = allData.map(_. product). distinct().
collect()

val bAllItemIDs = sc.broadcast( allItemIDs)

val model = ALS.trainImplicit( trainData, 10, 5, 0.01, 1.0)

val auc = areaUnderCurve( cvData, bAllItemIDs, model.predict)
```

k-Fold Cross-validation

- Create a k-fold partition of the dataset
  - For each of the k experiments use K-1 folds for training
    - The remaining fold for testing



True error estimate

- k-fold cross validation is similar to random subsampling
- The advantage of k-Fold Cross validation
  - All the examples in the dataset are eventually used for both training and testing
- The true error is estimated as the average error rate

$$E = \frac{1}{K}\sum_{i=1}^{K} E_i$$

k-Fold Cross-validation with Spark

- `MLUtils.kFold()`

```
def predictMostListened(
   sc: SparkContext,
   train: RDD[Rating])(allData:
RDD[( Int, Int)]) = {

   val bListenCount = sc.broadcast(
     train.map( r = > (r.product, r.rating)).
        reduceByKey(_ + _).collectAsMap()
   )
   allData.map { case (user, product) = >
     Rating(
        user, product,
        bListenCount.value.getOrElse(product, 0.0) )
   }
}
val auc = areaUnderCurve(cvData, bAllItemIDs,
        predictMostListened(sc,trainData))
```


Hyperparameter selection

- `MatrixFactorizationModel`
- `ALS.trainImplicit()`
- `rank = 10`
  - The number of latent factors in the model
  - The number of columns, k
- `iterations = 5`
  - The number of iterations that the factorization runs
- `lambda = 0.1`
  - A standard overfitting parameter
  - Higher value guards against overfitting
    - Values that are too high will decrease the factorization's accuracy
- `alpha = 1.0`
  - Controls the relative weight of observed versus unobserved user-product interactions in the factorization

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CASE STUDY: Recommendation Systems

Amazon.com : Item-to-item collaborative filtering

This material is built based on,

- Greg Linden, Brent Smith, and Jeremy York, "Amazon.com Recommendations, Item-to-Item Collaborative Filtering" IEEE Internet Computing, 2003

- Amazon.com uses recommendations as a targeted marketing tool
  - Email campaigns
  - Most of their web pages

Item-to-item collaborative filtering

- It does NOT match the user to similar customers
- Item-to-item collaborative filtering
  - Matches each of the user's purchased and rated items to similar items
  - Combines those similar items into a recommendation list

Determining the most-similar match

- The algorithm builds a similar-items table
  - By finding items that customers tend to purchase together
- How about building a product-to-product matrix by iterating through all item pairs and computing a similarity metric for each pair?
- Many product pairs have no common customer
  - If you already bought a TV today, will you buy another TV again today?

- Calculating the similarity between a single product and all related products:

```
For each item in product catalog, I1
  For each customer C who purchased I1
    For each item I2 purchased by customer C
      Record that a customer purchased I1 and I2
  For each item I2
    Compute the similarity between I1 and I2
```


Computing similarity

- Using cosine measure
  - Each vector corresponds to an item rather than a customer
  - M dimensions correspond to customers who have purchased that item

Creating a similar-item table

- Similar-items table is extremely computing intensive
  - Offline computation
  - $O(N^2M)$ in the worst case
    - Where N is the number of items and M is the number of users
  - Average case is closer to O(NM)
    - Most customers have very few purchases
  - Sampling customers who purchase best-selling titles reduces runtime even more
    - With little reduction in quality

Scalability

- Amazon.com has around 110 million active customers(244 million total customers) and several million catalog items
- Traditional collaborative filtering does little or no offline computation
- Online computation scales with the number of customers and catalog items.

http://www.fool.com/investing/general/2014/05/24/how-many-customers-does-amazon-have.aspx

Key scalability strategy for amazon recommendations

- Creating the expensive similar-items table offline
- Online component
  - Looking up similar items for the user's purchases and ratings
  - Scales independently of the catalog size or the total number of customers
- It is dependent only on how many titles the user has purchased or rated

Recommendation quality

- The algorithm recommends highly correlated similar items
  - Recommendation quality is excellent
  - Algorithm performs well with limited user data

Large scale data analysis using Spark

CASE STUDY: Linear Models

Spark's linear models

- Classification
  - Linear Support Vector Machines (SVMs)
  - Logistic regression
- Regression
  - Linear least squares, Lasso, and ridge regression

Implementation

- `SVMWithSGD`
- `LogisticRegressionWithBFGS`
- `LogisticRegressionWithSGD`
- `LinearRegressionWithSGD`
- `RidgeRegressionWithSGD`
- `LassoWithSGD`

Large scale data analysis using Spark

CASE STUDY: Linear Models

Linear Regression Model to a Large Dataset

The linear regression model

- The structure is exactly the same as for the linear discriminant function

$f(x) = w_0 + w_1x_1 + w_2x_2 + \ldots$

	A	B	C	D	E	F	G	H
Math score	85	85	62	67	89	65	80	67
Physics score	89	92	70	95	95	80	75	80

- How big is the error of the fitted model?
  - We would like to minimize this error

- The model that fits the data best
  - The model with **the minimum sum of errors** on the training data
  - e.g. The sum or mean of the squares of the errors
    - Least squares regression

Squared error

- Squared error
  - Strongly penalizes very large errors
  - Drawback
    - Is very **sensitive to the data**
    - Erroneous or outlying data points can severely skew the resultant linear function

- We should choose the objective function to optimize

Root Mean Squared Error

- Measures the differences between values predicted by model estimator and the values actually observed

$$RMSD = \sqrt{\frac{\sum_{i=1}^{n}(h_\theta(x^{(i)}) - y^{(i)})^2}{n}}$$

Linear Regression

- Calculating a linear regression
  - Using the least square criterion

	A	B	C	D	E	F	G	H
Math score	85	85	62	67	89	65	80	67
Physics score	89	92	70	95	95	80	75	80

$h_\theta(x) = \theta_0 + \theta_1 x_1$

where, the θs are the **parameters** (Math scores, or slopes)

Linear Regression -- continued

$$h(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 \ldots$$

- To simplify the notation,

$$h(x) = \sum_{i=0}^{n} \theta_i x_i$$

Objective function (Cost function)

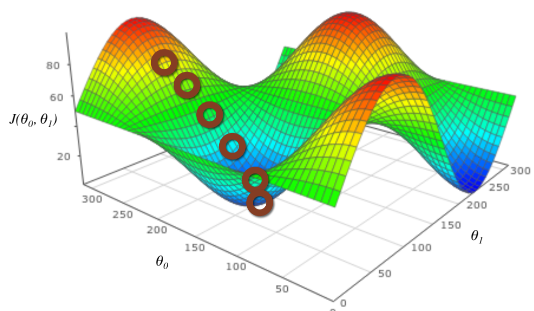
- For a given training set, how do we pick, or learn, the parameter θ?
- Make $h(x)$ close to y
  - Make your prediction close to the real observation
- We define the **objective (cost) function**

$$J(\theta) = \frac{1}{2}\sum_{i=0}^{m}(h_\theta(x^{(i)}) - y^{(i)})^2$$

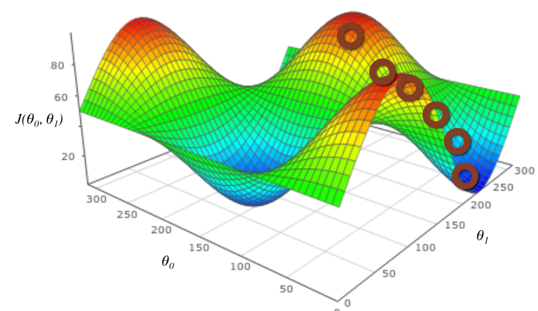
Minimization problem

- We have a function $J(\theta_0, \theta_1)$
- We want to find $\min_{\theta_0,\theta_1} J(\theta_0,\theta_1)$
- **Goal: Find parameters to minimize the cost (output of the objective function)**
- Outline of our approach:
  - Start with some θ_0, θ_1
  - Keep changing θ_0, θ_1 to reduce $J(\theta_0, \theta_1)$ until we end up at a minimum

Concept of Gradient descent algorithm (1/2)



Concept of Gradient descent algorithm (2/2)



Stochastic Gradient descent algorithm

Repeat until convergence {

$$\theta_j := \theta_j - \alpha\frac{\partial}{\partial\theta_j}J(\theta_0,\theta_1)$$

(for j=0 and j=1)

}

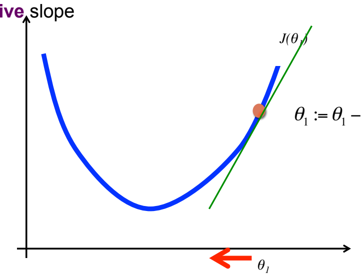
- Simultaneous update
  - Your implementation should perform simultaneous update
    - See slide 41

Simultaneous update

Correct: Simultaneous update	**Incorrect:**
temp0 := $\theta_0 - \alpha\frac{\partial}{\partial\theta_0}J(\theta_0,\theta_1)$	temp0 := $\theta_0 - \alpha\frac{\partial}{\partial\theta_0}J(\theta_0,\theta_1)$
	θ_0 := temp0
temp1 := $\theta_1 - \alpha\frac{\partial}{\partial\theta_1}J(\theta_0,\theta_1)$	temp1 := $\theta_1 - \alpha\frac{\partial}{\partial\theta_1}J(\theta_0,\theta_1)$
θ_0 := temp0 θ_1 := temp1	θ_1 := temp1

Decreasing θ_1

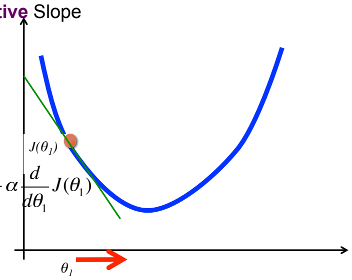
- **Positive** slope



$$\theta_1 := \theta_1 - \alpha \frac{d}{d\theta_1} J(\theta_1)$$

Increasing θ_1

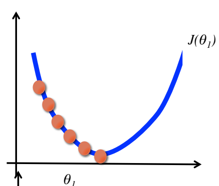
- **Negative** Slope



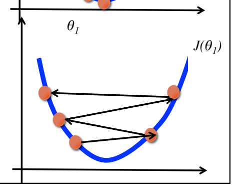
$$\theta_1 := \theta_1 - \alpha \frac{d}{d\theta_1} J(\theta_1)$$

Learning rates

- If α is too small, gradient descent can be slow

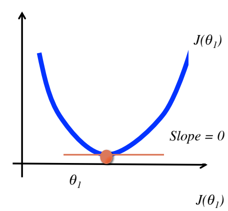


- If α is too large, gradient descent can overshoot the minimum
  - It may fail to converge
  - Or even diverge



Learning rates: starting at the optimal value?

- Current value of θ_1 has converged already
  - No more iteration required



Fixed learning rate α

- Gradient descent can converge to a local minimum, even with a fixed learning rate
- As we approach a local minimum, gradient descent will automatically take smaller steps
  - **No need to decrease** α over time

$$\theta_1 := \theta_1 - \alpha \frac{d}{d\theta_1} J(\theta_1)$$

Using Gradient Descent Algorithm for Linear Regression Model

Gradient descent algorithm

Repeat until convergence {

$$\theta_0 - \alpha \frac{\partial}{\partial \theta_0} J(\theta_0, \theta_1)$$

(for j=0 and j=1)

}

Linear Regression Model

$$h_\theta(x) = \theta_0 + \theta_1 x_1$$

$$J(\theta) = \frac{1}{2m} \sum_{i=0}^{m} (h_\theta(x^{(i)}) - y^{(i)})^2$$

$$\frac{\partial}{\partial\theta_j}J(\theta_0,\theta_1)=\frac{\partial}{\partial\theta_j}\frac{1}{2m}\sum_{i=1}^{m}(h_\theta(x^{(i)})-(y^{(i)}))^2$$

$$=\frac{\partial}{\partial\theta_j}\frac{1}{2m}\sum_{i=1}^{m}(\theta_0+\theta_1x^{(i)}-y^{(i)})^2$$

Case 1, θ_0 $(j=0)$:

$$\frac{\partial}{\partial\theta_0}J(\theta_0,\theta_1)=\frac{\partial}{\partial\theta_0}\frac{1}{2m}\sum_{i=1}^{m}(h_\theta(x^{(i)})-(y^{(i)}))^2=\frac{1}{m}\sum_{i=1}^{m}(h_\theta(x^{(i)})-(y^{(i)}))$$

Case 2, θ_1 $(j=1)$:

$$\frac{\partial}{\partial\theta_1}J(\theta_0,\theta_1)=\frac{\partial}{\partial\theta_0}\frac{1}{2m}\sum_{i=1}^{m}(h_\theta(x^{(i)})-(y^{(i)}))^2=\frac{1}{m}\sum_{i=1}^{m}(h_\theta(x^{(i)})-(y^{(i)}))x^{(i)}$$

Gradient descent for Linear Regression

Repeat until convergence {

$$\theta_0 := \theta_0-\alpha\frac{1}{m}\sum_{i=1}^{m}(h_\theta(x^{(i)})-y^{(i)})$$

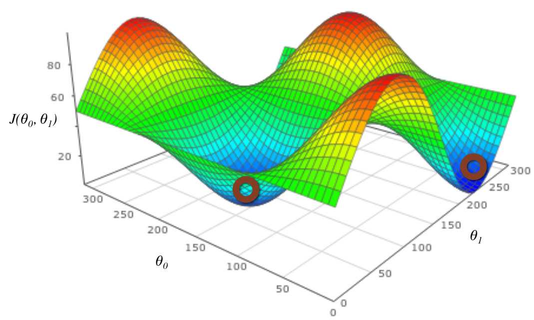
$$\theta_1 := \theta_1-\alpha\frac{1}{m}\sum_{i=1}^{m}(h_\theta(x^{(i)})-y^{(i)})x^{(i)}$$

(for j=0 and j=1)

}

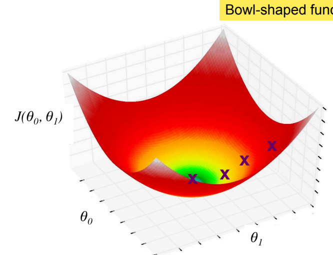
Update θ_0 and θ_1 simultaneously

Multiple local optimal points

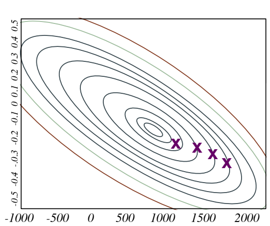


Convex function

Bowl-shaped function

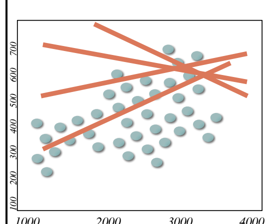


$J(\theta_0,\theta_1)$

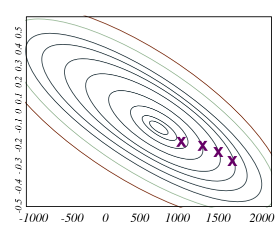


Fitting $h_\theta(x)$

$h_\theta(x)$



$J(\theta_0,\theta_1)$



"Batch" Gradient Descent

- Batch
  - Each step of gradient descent uses all of the training example

$$\theta_j := \theta_j + \alpha \frac{1}{m} \sum_{i=1}^{m} (y^{(i)} - h_\theta(x^{(i)})) x_j^{(i)}$$

Running with Spark in parallel

- For the sample size 1,000 (m=1,000)

- Batch gradient descent:

$$\theta_j := \theta_j + \alpha \frac{1}{1{,}000} \sum_{i=1}^{1000} (y^{(i)} - h_\theta(x^{(i)})) x_j^{(i)}$$

- Using 4 machines

continued

- Step 1. 4 input splits
- $(x^{(1)},y^{(1)}),\ldots,((x^{(250)},y^{250)})$
- $(x^{(251)},y^{(251)}),\ldots,((x^{(500)},y^{500)})$
- $(x^{(501)},y^{(501)}),\ldots,((x^{(750)},y^{750)})$
- $(x^{(751)},y^{(751)}),\ldots,((x^{(1000)},y^{1000)})$

- Step 2. Calculate temp1 ~ 4

- Step 3. Calculate final results

$$temp1 = \sum_{i=1}^{250} (y^{(i)} - h_\theta(x^{(i)})) x_j^{(i)}$$

$$temp2 = \sum_{i=1}^{500} (y^{(i)} - h_\theta(x^{(i)})) x_j^{(i)}$$

$$temp3 = \sum_{i=1}^{750} (y^{(i)} - h_\theta(x^{(i)})) x_j^{(i)}$$

$$temp4 = \sum_{i=1}^{1000} (y^{(i)} - h_\theta(x^{(i)})) x_j^{(i)}$$