# Prediction as a service with Ensemble Model trained in SparkML and Python ScikitLearn on 1Bn observed flight prices daily

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https://www.youtube.com/watch?v=h9cQTooY92E

# What is this talk about?


- Ensemble approach for large scale DataScience
  - Online learning for huge datasets
  - thousands simple models are better than one very complex
- N-billion rows/day machine learning system architecture
  - Implementation of parallel online training of tens of thousands of models in Spark Streaming and Python ScikitLearn

# Ensemble approach on billions of rows

# Batch vs Online model training

**Batch**

Bn $\begin{pmatrix} x_{11} & \cdots & x_{1p} \\ x_{21} & \cdots & x_{2p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{np} \end{pmatrix}$

- Large variety of options available (historical reasons)
- Often more accurate
- Does not scale well
- **Model might be missing critical latest information**

**Online**

can stream

Bn Mn $\begin{pmatrix} x_{11} & \cdots & x_{1p} \\ x_{21} & \cdots & x_{2p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{np} \end{pmatrix}$

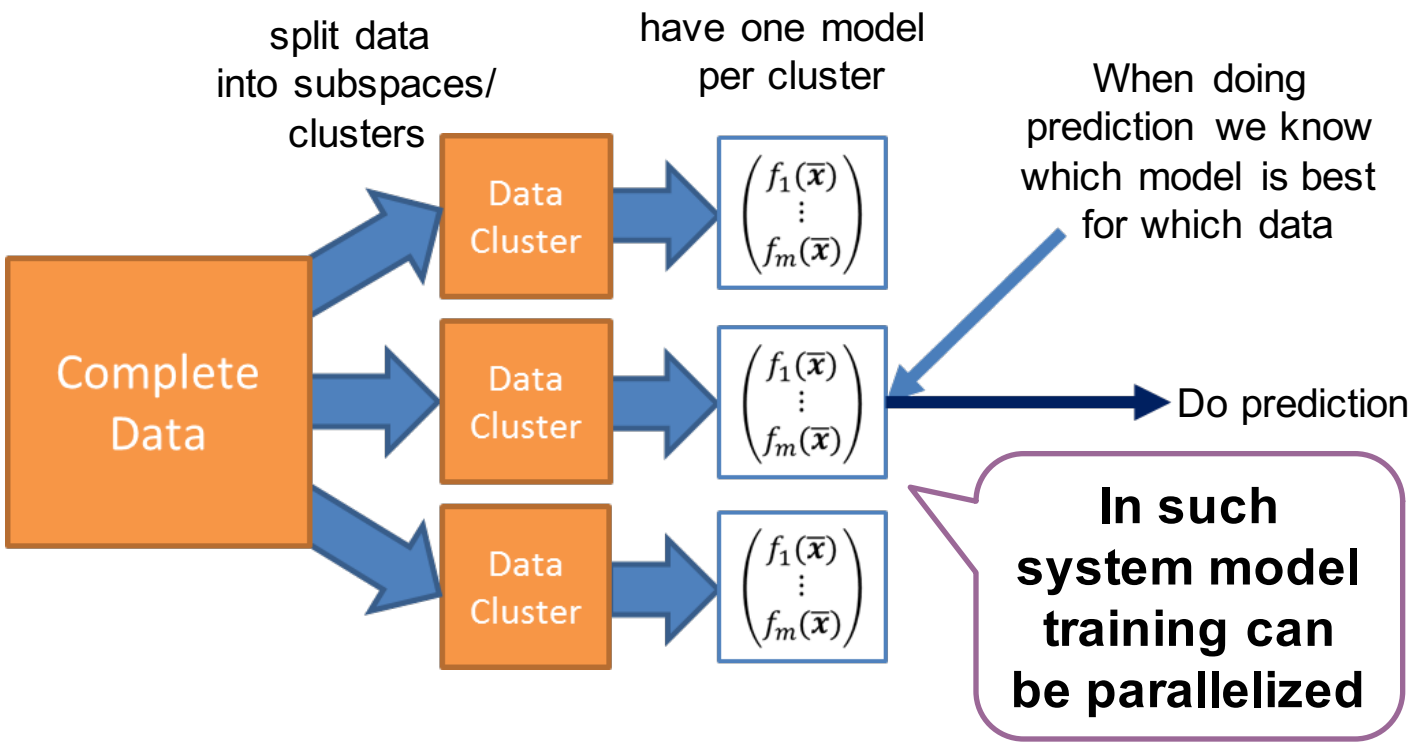
$\begin{pmatrix} x_{11} & \cdots & x_{1p} \\ x_{21} & \cdots & x_{2p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{np} \end{pmatrix}$

$\begin{pmatrix} x_{11} & \cdots & x_{1p} \\ x_{21} & \cdots & x_{2p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{np} \end{pmatrix}$

- Train on microbatches or individual observations
- Relies on Learning Rate and Sample Weighing
- Can be used in horizontally scalable environments
- **Model can be as up to date as possible**

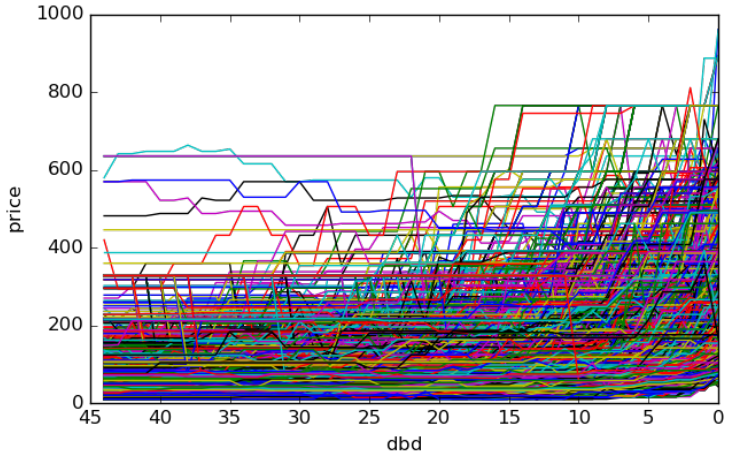
**Especially critical in prediction of volatile signals**

# Ensemble approach to prediction in BigData



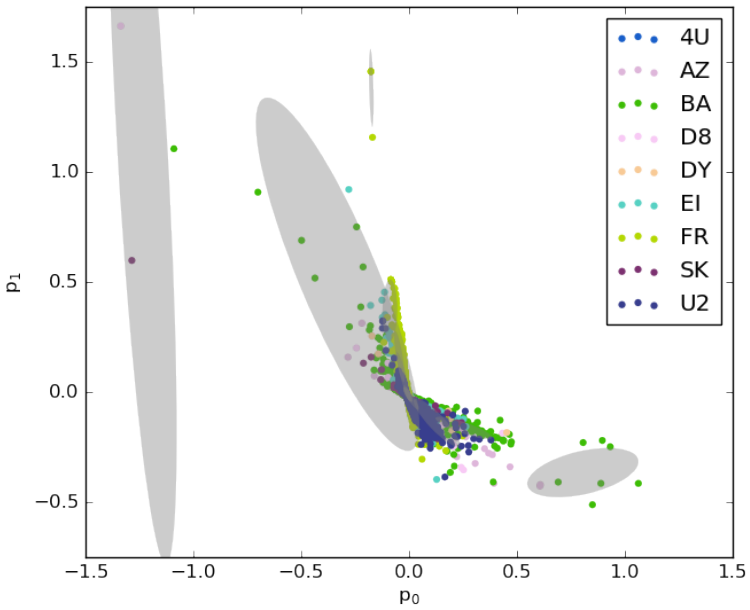

traditional ensemble mixes multiple models for one prediction, here we simply select one best for the data segment

# Segmenting the space




- Entire space consists of 1.2Bn time series
- Best results obtained when division is done using combination of knowledge (manual division) and clustering methods
- Optimal number of slices/clusters is between few thousand to hundreds of thousands
- Clustering methods need dimensionality reduction if subspace has still too many dimensions

# Gaussian Mixture Model

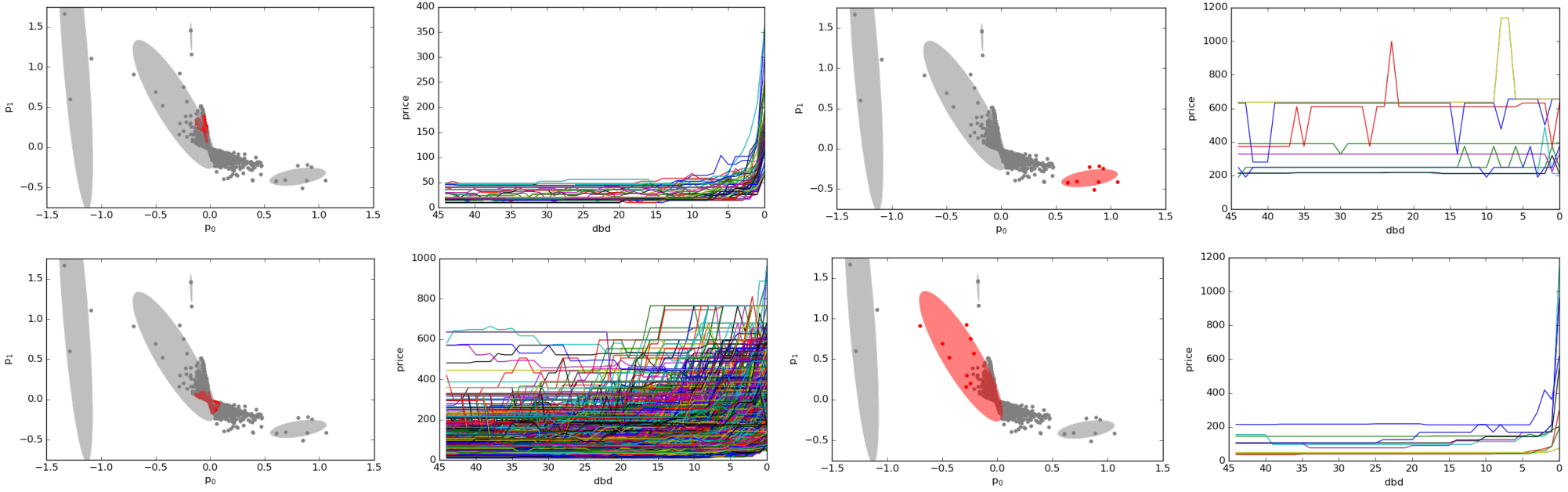



(showing only 2 first parameters)

- Fuzzy clustering method which gives probability of a point being in the cluster
- The probability could be used as a model weight, in case of model mixing

SparkML: org.apache.spark.ml.clustering.GaussianMixture
http://spark.apache.org/docs/latest/ml-clustering.html#gaussian-mixture-model-gmm

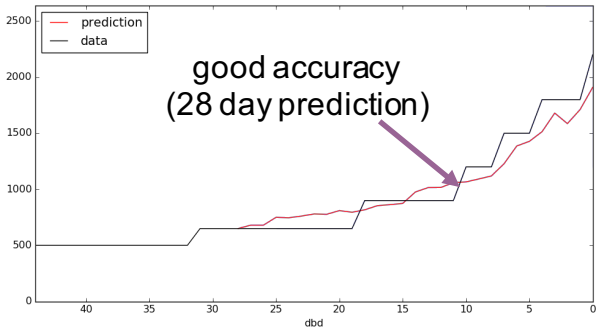
# Gaussian Mixture Model Results

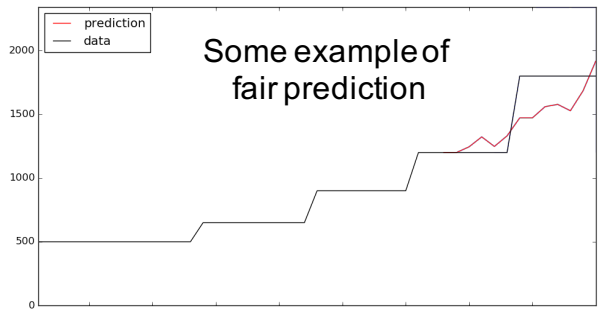


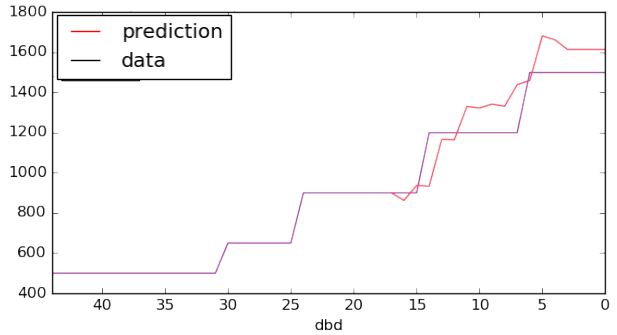
# Feature and model selection

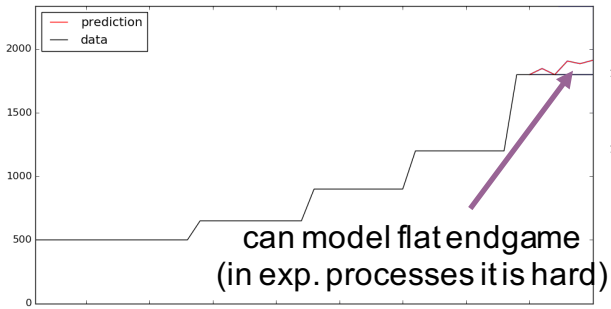
- OneHotEncoder:
  - can capture any nonlinear behavior
  - explodes exponentially dims
  - can reduce your problem to a hypercube
- Try assigning values to labels which carry information
  - $hour \in [0, 1, \ldots, 23] \rightarrow hour' \in [0.22, 0.45, \ldots, 0.03]$
- Try to capture nonlinear behavior using linear model, by adding meta-features
- Classification vs regression
  - if your problem can be converted into classification, try this as a first attempt
- Linear online models in Python:
  - sklearn.linear_model.SGDClassifier
    http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.SGDClassifier.html
  - sklearn.linear_model.SGDRegressor
    http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.SGDRegressor.html
- Other interesting models:
  - whole sklearn.svm package
  - Kalman and ARIMA models
  - Particle Predictor (wrote own library)

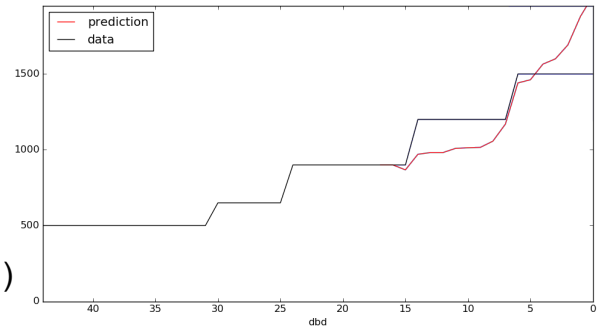
# Prediction results

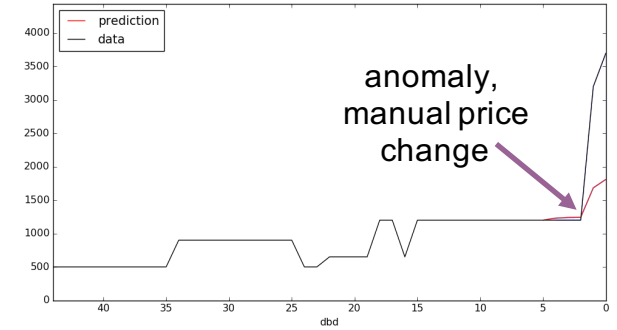


# N-billion rows/day machine learning architecture using DataBricks

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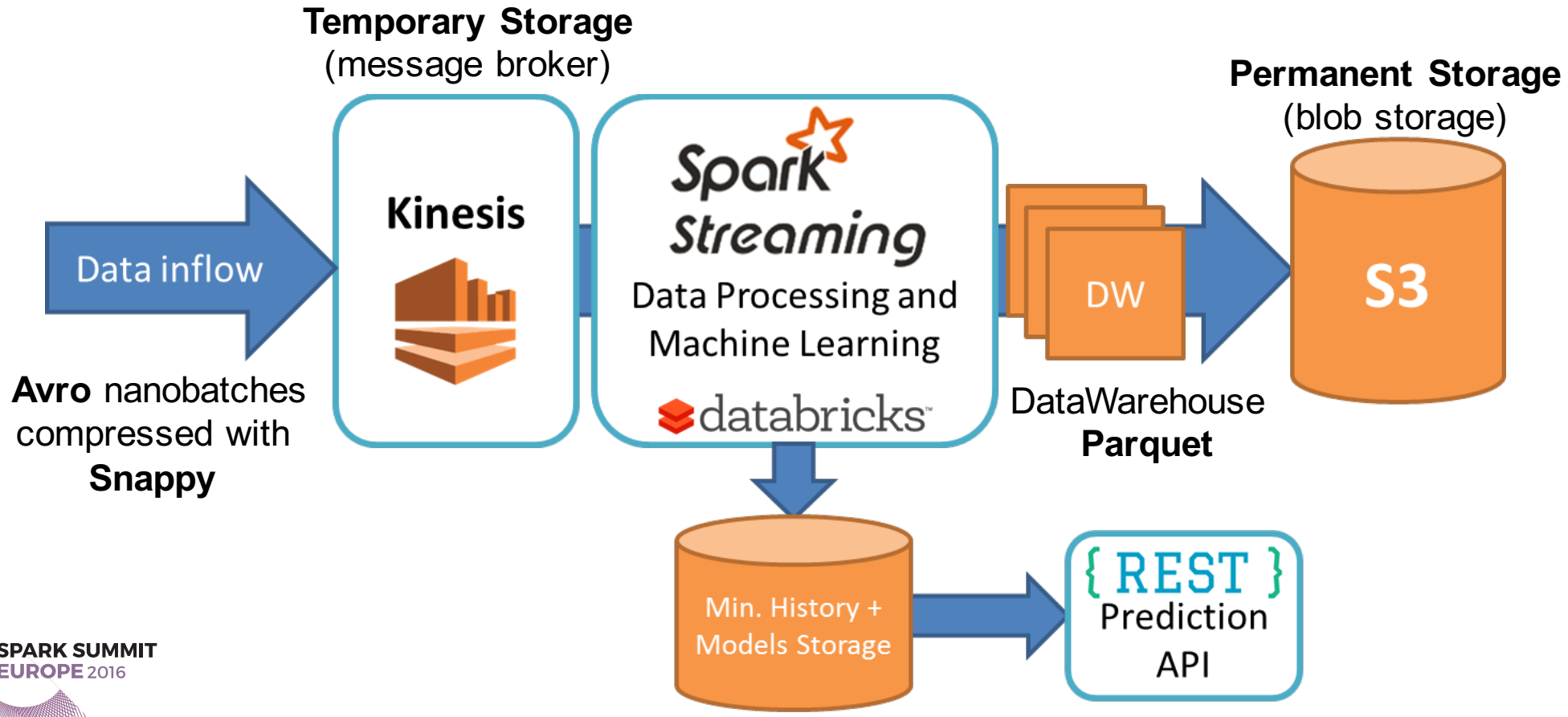
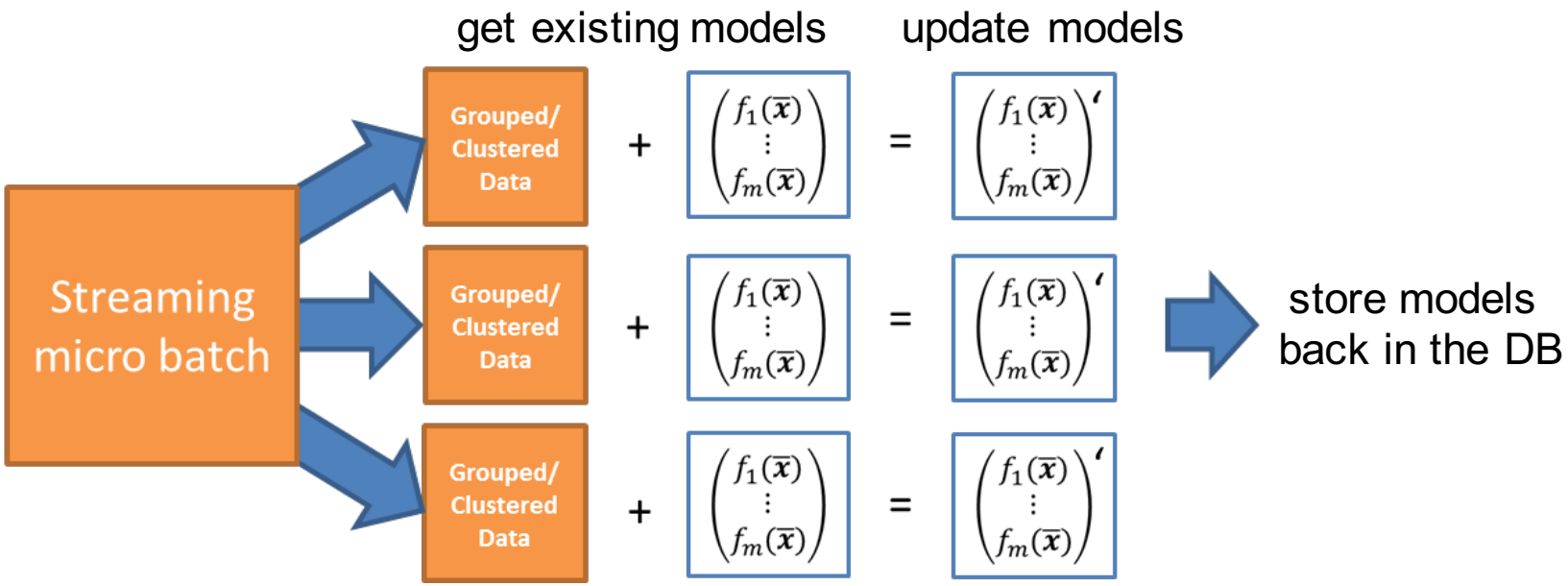


# Training models in parallel in Spark Streaming






* we already know the clusters

# Grouping in Spark DataFrames with collect_list()

```
> # FLight TimeSeries DataFrame
  fltsdf = dspmin \
    .groupBy("cluster_id") \
    .agg(
         expr("collect_list(days_before_departure) as
  days_before_departure_list"),
         expr("collect_list(price_inc) as price_inc_list"),
         expr("count(price_inc) as price_count"),
         expr("min(days_before_departure) as days_before_departure_min"),
         expr("max(days_before_departure) as days_before_departure_max")
        )
```

| cluster_id | days_before_departure | price_inc | price_exc |
|---|---|---|---|
| 345130379 | 18 | 404 | 380 |
| 345130379 | 24 | 60 | 34 |
| 345130379 | 26 | 128 | 102 |
| 345130379 | 29 | 240 | 214 |
| 345130379 | 40 | 352 | 326 |
| 345130379 | 42 | 124 | 100 |
| 345130379 | 86 | 270 | 244 |
| 345130379 | 103 | 242 | 216 |
| 345130379 | 104 | 218 | 194 |

| cluster_id | days_before_departure_list | price_inc_list | price_exc_list |
|---|---|---|---|
| 1780623700 | [0,1,2,3,4,5,6,7,8,9,10,11,12,1 | [158,134,112,112,92,62,52, | [158,134,112,112,92,62,52 |
| 268037612 | [0,1,2,5,6,7,8,9,12,13,14,15,1 | [66,46,46,46,18,18,18,18,1 | [66,46,46,46,18,18,18,18, |
| -2009081663 | [0,1,4,5,6,7,8,11,12,13,14,15, | [240,134,92,66,66,66,46,32 | [240,134,92,66,66,66,46,3 |
| -634639582 | [0,1,2,3,4,5,6,7,8,9,10,11,12,1 | [66,34,28,28,32,18,16,14,1 | [66,34,28,28,32,18,16,14, |
| 1411515385 | [0,3,4,5,6,7,10,11,12,13,14,15 | [190,112,112,92,92,92,78,6 | [190,112,112,92,92,92,78, |
| -286460299 | [0,1,2,3,6,7,8,9,10,13,14,15,1 | [240,240,240,158,92,92,78, | [240,240,240,158,92,92,7 |
| -610713405 | [0,3,4,5,6,7,10,11,12,13,14,17 | [134,66,66,60,34,34,32,26, | [134,66,66,60,34,34,32,26 |
| 1190364950 | [0,3,4,5,6,7,10,11,12,13,14,17 | [158,158,134,112,78,92,66, | [158,158,134,112,78,92,6 |

# Wrapping model training in UDF

```
sgdlinreg_models = flt \
  .withColumn("sgdlinreg", sgdlinreg_udf(
      flt.cluster_id,
      flt.price_inc_list_zoh,
      flt.price_inc_list_lag1,
      flt.price_inc_list_lag2,
      flt.price_inc_list_lag3,
      flt.price_inc_list_lag4,
      flt.price_inc_list_lag5,
      flt.price_inc_list_lag6,
      flt.price_inc_list_lag7
    ))

display(sgdlinreg_models.select("sgdlinreg"))
```

| cluster_id | days_before_departure_list | price_inc_list | price_exc_list |
|---|---|---|---|
| 1780623700 | [0,1,2,3,4,5,6,7,8,9,10,11,12,1 | [158,134,112,112,92,62,52, | [158,134,112,11 |
| 268037612 | [0,1,2,5,6,7,8,9,12,13,14,15,1 | [66,46,46,46,18,18,18,18,1 | [66,46,46,46,18 |
| -2009081663 | [0,1,4,5,6,7,8,11,12,13,14,15, | [240,134,92,66,66,66,46,32 | [240,134,92,66, |
| -634639582 | [0,1,2,3,4,5,6,7,8,9,10,11,12,1 | [66,34,28,28,32,18,16,14,1 | [66,34,28,28,32 |
| 1411515385 | [0,3,4,5,6,7,10,11,12,13,14,15 | [190,112,112,92,92,92,78,6 | [190,112,112,92 |
| -286460299 | [0,1,2,3,6,7,8,9,10,13,14,15,1 | [240,240,240,158,92,92,78, | [240,240,240,1 |
| -610713405 | [0,3,4,5,6,7,10,11,12,13,14,17 | [134,66,66,60,34,34,32,26, | [134,66,66,60,3 |

| sgdlinreg |
|---|
| [0.312164452051516,0.2500195199688649,0.14696794292077753,0.0739774484 |
| [0.13338744526183177,0.12112968431128747,0.11130912766696988,0.10185600 |
| [0.23559433475348757,0.19604764243883754,0.1619729900436198,0.123211434 |
| [-0.10016315603086957,-0.16458613496443103,-0.27811271711971636,-0.33133 |
| [0.14668838712780405,0.13123599721355966,0.12017499750599304,0.0993076 |
| [1.168599501383796,0.4523697946893281,0.5174869129611258,0.494670248349 |
| [0.15681717241410567,0.13897152879352645,0.11634114582885006,0.10410808 |

# Wrapping model training in UDF

```
> def sgdlinreg(cluster_id, x0, x1, x2, x3, x4, x5, x6, x7):

    # create a data matrix from columns
    X = np.transpose(np.matrix([x1, x2, x3, x4, x5, x6, x7]))

    # normalize the data
    X = normalize_using_db_norm(cluster_id, X)
    Y = np.reshape(normalize_using_db_norm(cluster_id, x0)[0],\
                   (1, len(x0)))[0]

    # generate sample weights to adjust the learning rate
    sample_weights = generate_sample_weights(X)

    # get the model:
    sgd_model = get_sgdregressor_from_db(cluster_id)

    # model train
    sgd_model.partial_fit(X, Y, sample_weights)

    # copy the coeffs (list of numpy floats) into native list
    # of python doubles (for Spark type compatibility)
    retval = []
    [retval.append(p.item()) for p in sgd_model.coef_]

    return(retval)

  sgdlinreg_udf = udf(sgdlinreg, ArrayType(DoubleType()))
```

Prepare the Matrix with inputs for model training

Normalize the data using normalization defined for this particular cluster

Generate sample weights which enable controlling the learning rate

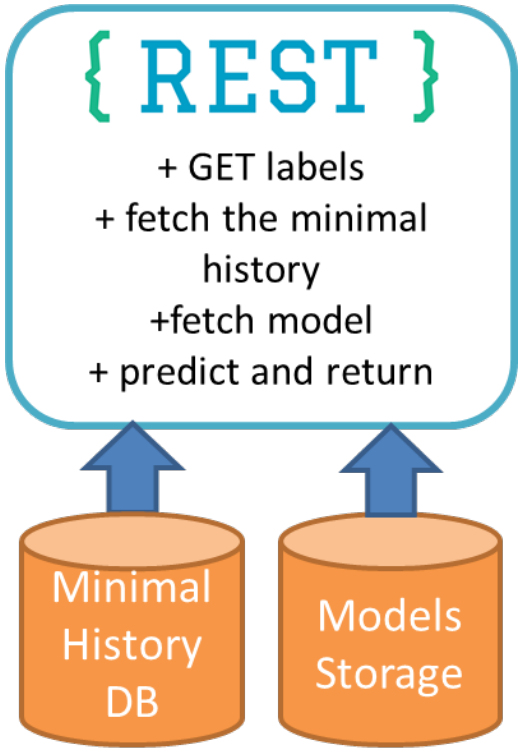
Get the current model from DB (use in memory DB for fast response)

Preform partial fit using the sample weights

Important trick:
Converts numpy.ndarray[numpy.float64] into native python list[float] which then can be autoconverted to Spark List[Double]

Register UDF which returns Spark List[Double]

# Time Series Prediction as a Service




- Provided the labels identify time series and lookup the model
- Get historical data (performance is the key)
- Recursively predict next price, shifting the window for the desired length

$$f\begin{pmatrix} x_{n-l} \\ \vdots \\ x_n \end{pmatrix} = x_{n+1} \Rightarrow f\begin{pmatrix} x_{n-l+1} \\ \vdots \\ x_{n+1} \end{pmatrix} = x_{n+2} \Rightarrow \ \ldots$$

- The same workflow for any model: SGDClassifier, SGDRegressor, ARIMA, Kalman, Particle Predictor

# Summary


- **Spark + Python is AWESOME for DataScience ☺**
- **Large scale DataScience needs correct infrastructure** (Kafka-Kinesis, Spark Streaming, in memory DB, Notebooks)
- It is much easier to work with large volumes of models, then very few ones
- Gaussian Mixture is great for fuzzy clustering, has very mature and fast implementations
- Spark DataFrames with UDF can be used to efficiently palletize the model training in tens and even hundreds of thousands models

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# THANK YOU!

# Q/A

## Remember, we are hiring!

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