Big Data Analytics for Semiconductor Manufactoring

BDC103C
NULL

February 3, 2015

Outline

Problem Definition

Given *Carrier*, *Chamber*, *Fab*, *Recipe*, *Tool* and tremendous amount of *FDC* data, we aim to:

- Create **novel** and **realistic** high dimensional data mining framework
- **Precisely** predict the value of CP
- Obtain the **decisive** factors that determine the outcome

Proposed Framework

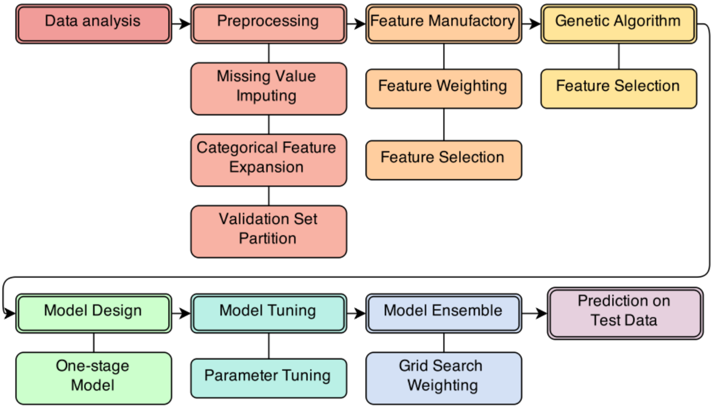


Figure: our framework

Missing Value Imputation

Categorical Features

- Most frequent elements

Numerical Features

- Average value of elements

Time-series Features

- Median value of neighbor instances

Categorical Feature Expansion

For range-based model, such as SVM.

Take *Chamber* feature for example:

- Original: $\begin{bmatrix} chamber1 \\ chamber2 \\ \vdots \end{bmatrix}$
- Expanded: $\begin{bmatrix} 1 & 0 \\ 0 & 1 \\ \vdots & \vdots \end{bmatrix}$

Validation Set

Prepare a hold-out set to validate our internal performance

Figure: subtrain and validation

How do we determine the portion of validation set / training set?

- Each instance get $\frac{1}{n}$ probability of being training data
- $\lim_{n \to \infty}(1 - \frac{1}{n})^n = \frac{1}{e} = 0.368$
- We use 0.368 training data as validation set and leave the rest as subtrain

High dimensional data

Two well-known methods for dealing with high dimensional data:

- Dimension reduction, such as PCA, auto-encoder, ...
- Feature selection

Discussion:

- Main difficulty of applying dimension reduction is its huge complexity; and there is no performance guarantee. (**time-consuming**)
- In contrast, applying feature selection based method can solve this problem. (**realistic**)
- Feature selection will also boost regressor performance. (**effective**)

Bunch of file selection

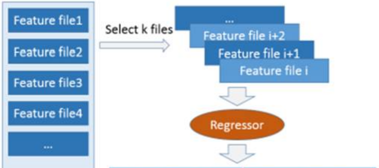
Lots of feature available. How can we extract meaningful features?

- **Divide**:
  - Sample a portion of features
- **Conquer**:
  - Extract meaningful features
  - Maintain importance in a table

Bunch of file selection

How can we extract meaningful features?

- Based on feature importance in certain regressor (tree-based model usually)



File # - Feature #	Regressor importance
File 1 – 1st dim	9.8
File 1 – 2nd dim	5.4
...	...

Figure: first-stage feature selection

Discussion

How do we fill values in the feature importance table?

- Divide and **Conquer**?
  - Fill the importance of features from tree-based model directly.

Discussion

How do we fill values in the feature importance table?

- **Divide** and **Conquer**?
  - Fill the importance of features from tree-based model directly. (X)
- Divide and Conquer:
  - Performance of each model reflects the behavior of a small subset of features.
  - Normalization is needed!!
- Feature Importance$[f_i] = \frac{\text{Regressor Importance}[f_i]}{\text{Feature Set Performance}[f]}\ \forall$ subset f

Compact Genetic Algorithm

What will we do next?

- The previous method is based on regressor importance.
  That is, we can abandon what our model cannot learn from.
- However, we want to further obtain which feature is **decisive**.
  That is, we want to optimize:

$$\underset{\text{featureSet}}{\operatorname{argmax}} \text{Regressor Performance}(\text{featureSet})$$

Compact Genetic Algorithm

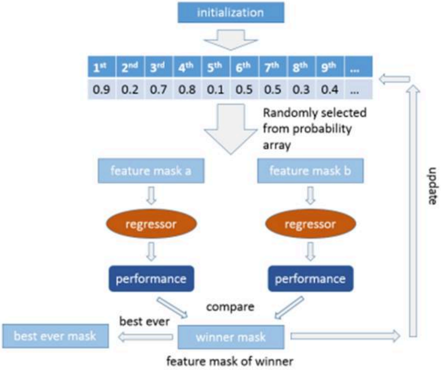


Figure: second-stage feature selection

Tree-based Model

Gradient Boosting Machine (GBM)

- Iteratively build new trees to correct current error
- Well performance in many data mining competition
  - Best performance in preliminaries in our experiment

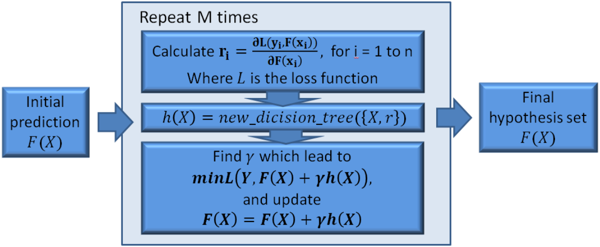


Figure: GBM workflow

Kernel-based Model

Support Vector Regression (SVR)

- Extended from SVM
- Find the hyperplane in feature space having minimized loss
  - Optimization function (primal):

$$\min_{\mathbf{w},b} \frac{1}{2}\|\mathbf{w}\|^2$$
$$\text{subject to } |y_i - \mathbf{w} \cdot x_i - b| \leq \epsilon \ \forall i$$

- Kernel trick
  - Project feature space to higher dimensional space
  - For example, linear kernel, polynomial kernel, RBF kernel, etc.
    - Linear kernel has the best performance in our experiment

Parameter Turing

Grid Search

- Try different combination of parameters
- Put measurement on a fix validation set
- GBM
  - **Tree number, shrinkage**
  - Decide the depth of model
- SVR with linear model
  - **Cost**
  - Decide the fitness of model, in terms of training data

Ensemble

Grid Search

- Give different weight ($1 \sim 10$) to the prediction of different model
  - Models we use: RF, GBM, SVR (Linear and RBF kernel)
- Put measurement on a fix validation set
- In our experiment, we find that RF and SVR with RBF kernel have 0 weight when we get obtain the best performance

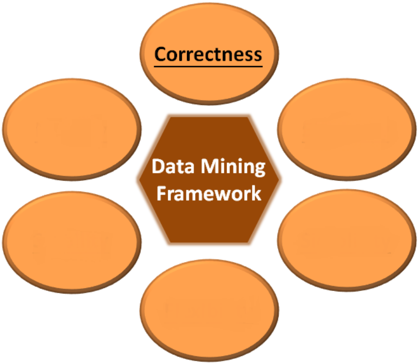
Performance

We take the ensemble result as our final submission

Model	Parameter	MSE (validation)
GBM	N_trees=3000, shrinkage=0.015	2.01
SVR (linear kernel)	Cost=1e-4	2.23
Ensemble	GBM weighted 2, SVR (linear) weighted 1	1.97

Figure: performance comparison

Conclusion



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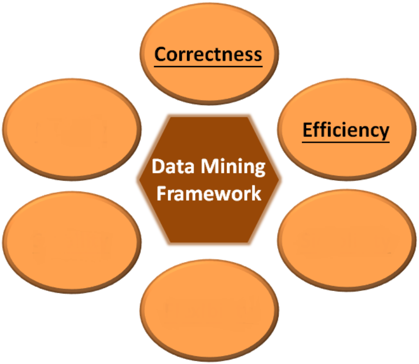

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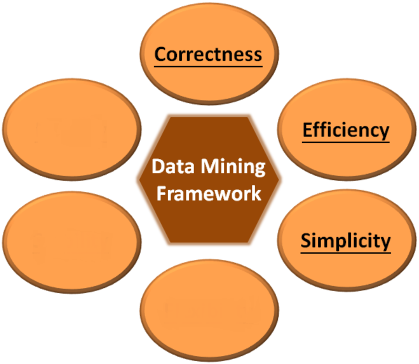
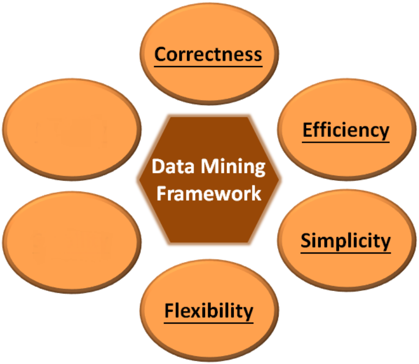

Correctness
Efficiency
Data Mining Framework
Simplicity

Conclusion


Correctness
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Conclusion


Correctness
Efficiency
Simplicity
Flexibility
Stability
Data Mining Framework

Conclusion


Correctness
Novelty
Efficiency
Data Mining Framework
Stability
Simplicity
Flexibility