Data-driven Sales Leads Prediction

for Everything-as-a-Service in the Cloud

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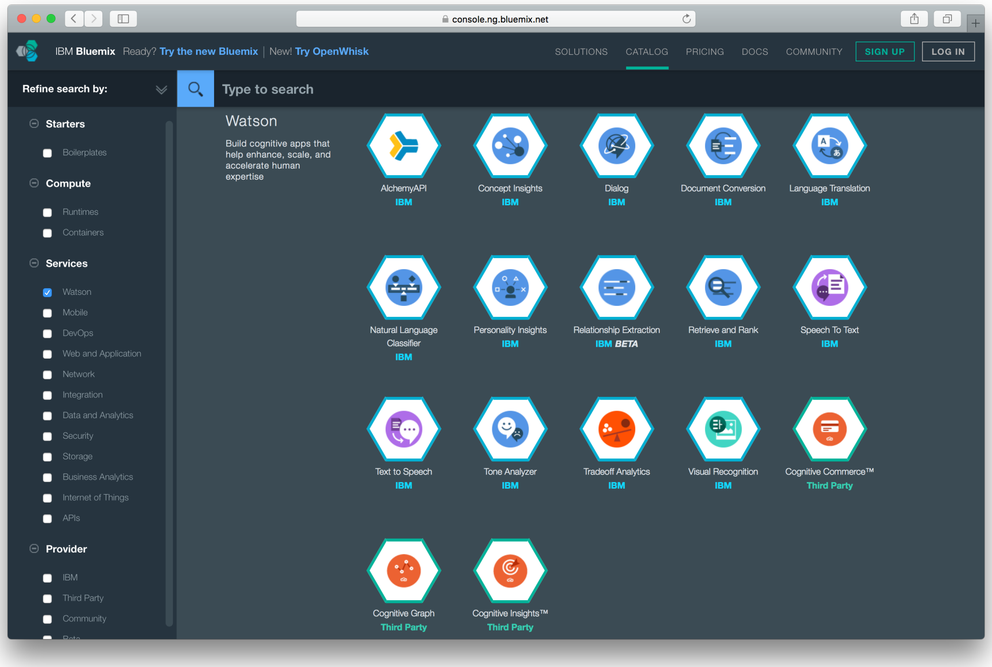
IBM Bluemix

- A **hybrid cloud development platform** to access a catalog of services and APIs, on which customers can build and run their apps
- It is a **compelling** platform:
  - **Widest selection** of compute choices for scalable, enterprise production apps such as bare metal, virtual servers, cloud foundry, and containers
  - **Big data and analytics for insights** beyond all needs
  - **Watson** for instant cognitive capabilities into apps and services
  - Over **one million** visiting customers



Cognitive Era with IBM Bluemix

- **IBM Bluemix** helps to run scalable analytics solutions like Streaming Analytics or AlchemyData News to get results in seconds.
- You can improve decisions and outcomes with Retrieve and Rank.

Streaming Analytics

Retrieve and Rank

AlchemyData

Geospatial Analytics

more information: https://developer.ibm.com/academic/resources/big-data-bluemix-educator-guide/

Challenge

IBM Bluemix is **growing rapidly** in popularity, but …

- A key challenge is how to **engage with a huge number of customers** while optimizing sales and marketing performance.
- It is nearly impossible to understand behaviors of the customers without **an inter-team collaboration** among various stakeholders.

On top of these challenges …

DDBA Challenge

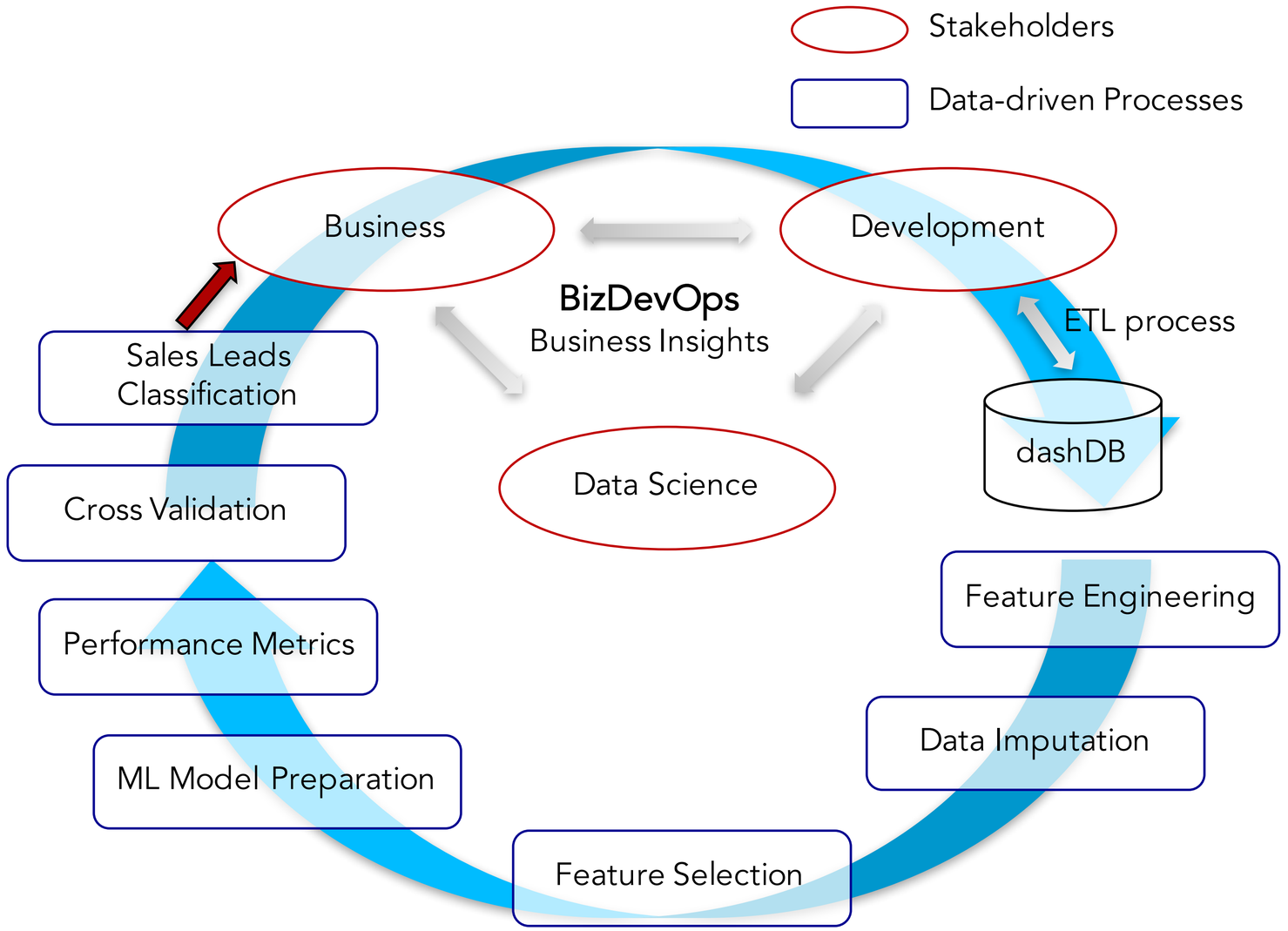
Additional challenges to **recognize high profile customers** in Data-driven Business Analysis (DDBA):

- **heavy customer traffic flows**
- conversion to **meaningful and consumable** features
- handling **missing values** of some customer behaviors
- **class imbalance problem** – the actual paying customer class represented by only a few tuples
- constantly **changing environment** – business models (providing services) and user behaviors

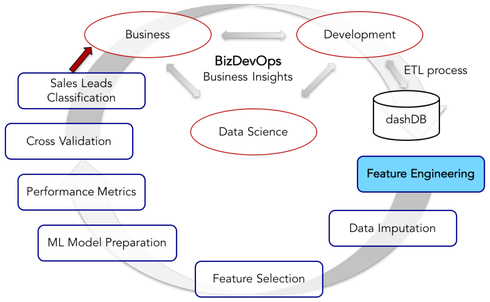
Iterative Prediction Framework

BizDevOps – fills in the gap between the actual business goals and DevOps deliverables.

Iterative – to adapt to a continuously changing environment.



Feature Engineering (1)

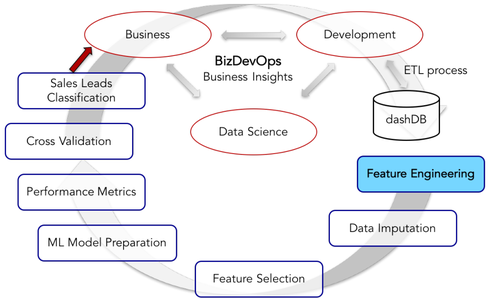


- application creation
- application update
- service creation
- service binding creation
- service binding deletion
- service usage
- runtime usage

RFD Analysis

Recency + Frequency + Duration

Feature Engineering (2)



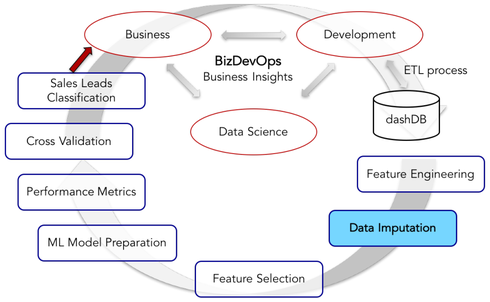
- customer account
- applications
- services

L Analysis

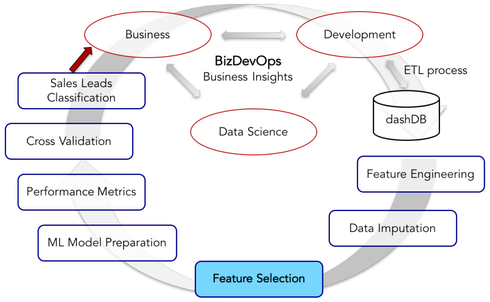
Lifetime

total **24** features

Data Completion

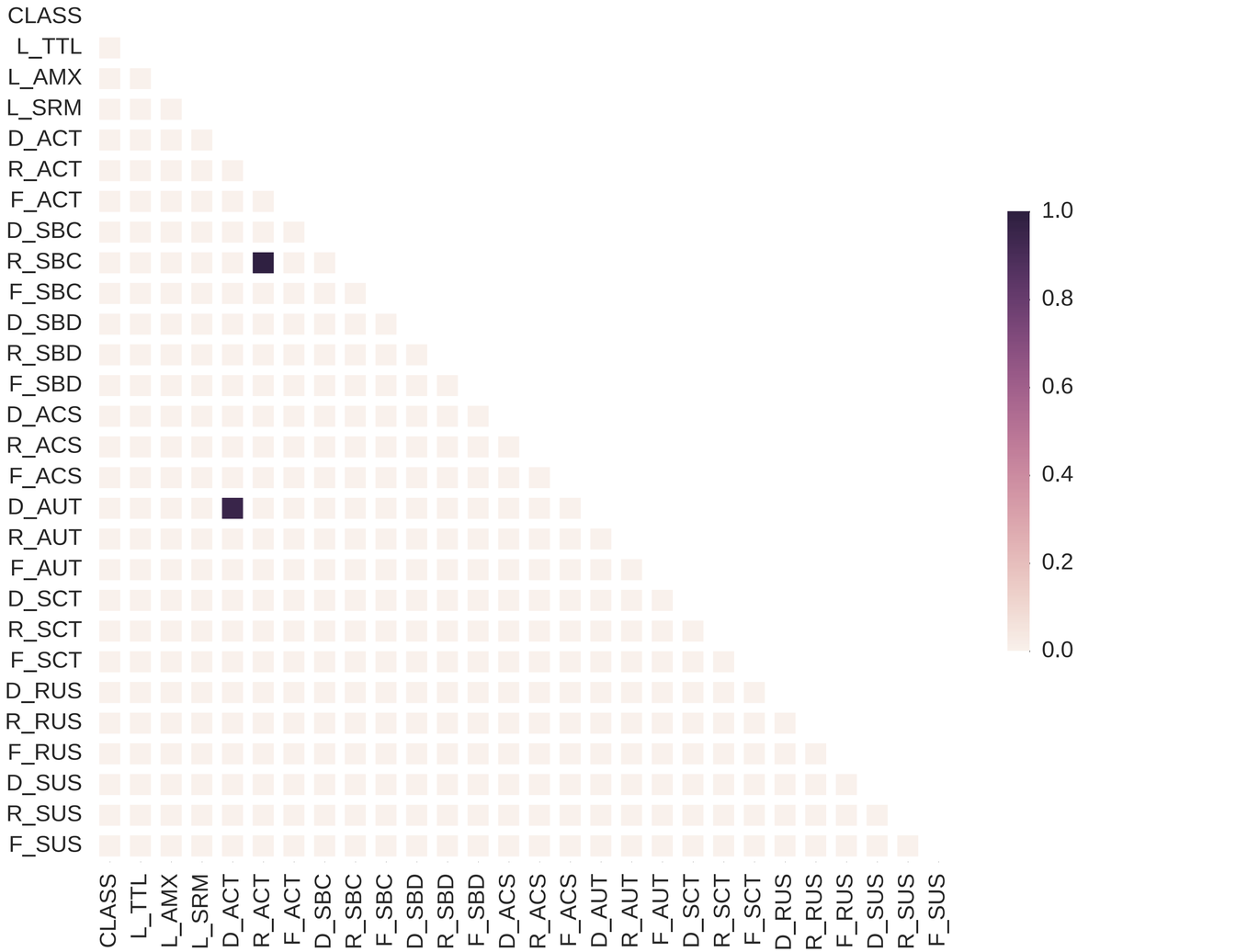


- Ignoring instances having null values
- null values to the mean of close group
- **null values to max or min of values** – in the way which least affects the data
  - less Recency/Duration values more informative, so max of values for the attributes
  - bigger Frequency/Lifetime values more informative, so min of values for the attributes

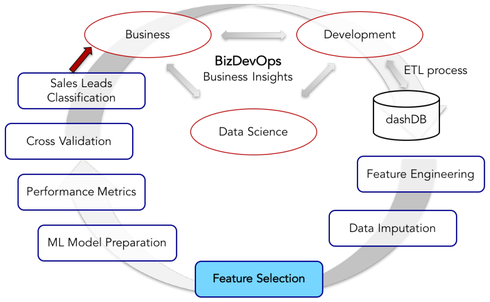


Feature Selection – C_95

Using **Pearson's correlation**, eliminate highly correlated features: (R_SBC, R_ACT*) and (D_ACT, D_AUT*) **over THR. |0.95|**



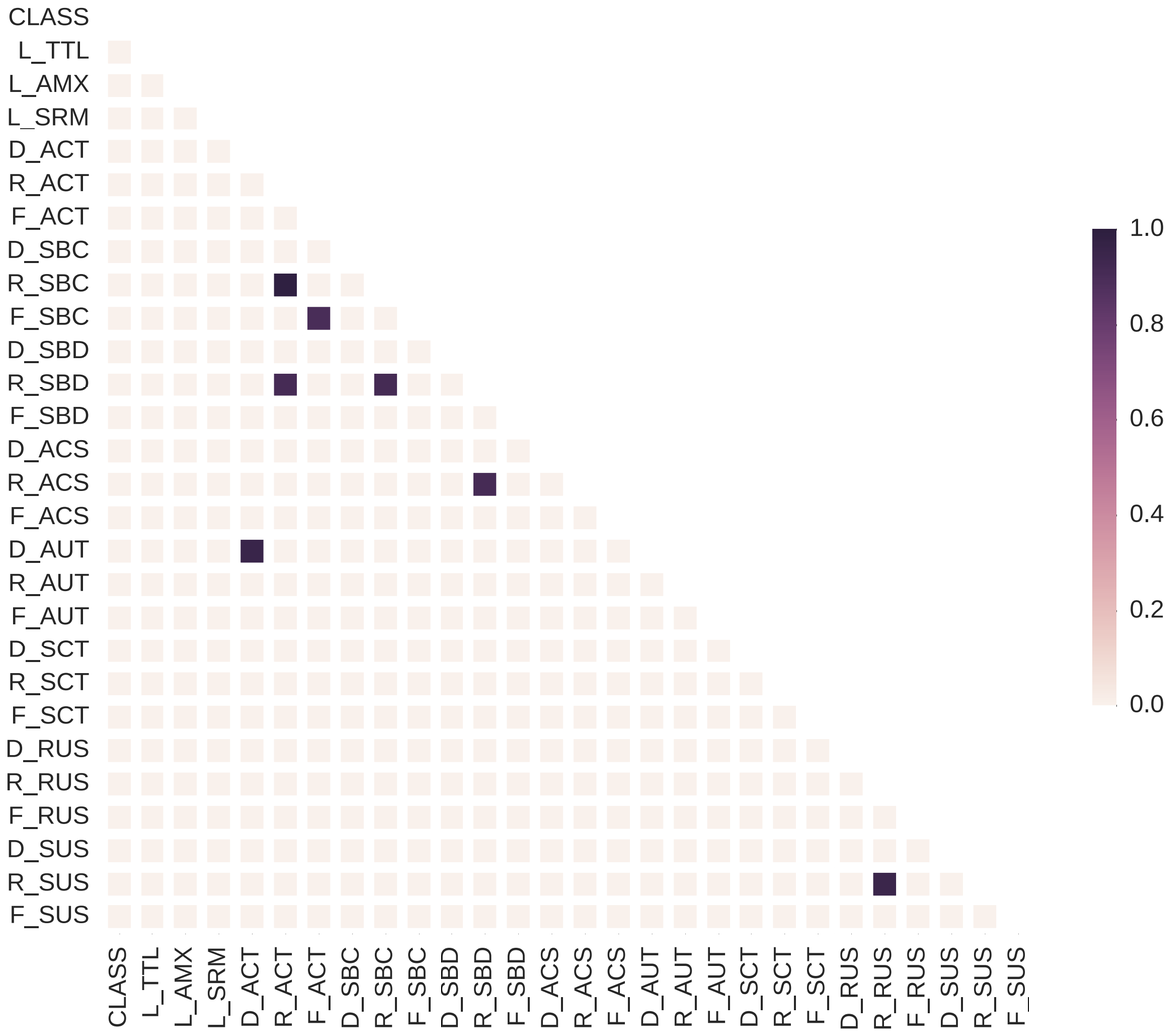
* We dropped the red ones.



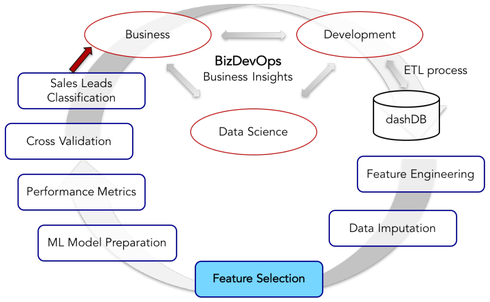
Feature Selection – C_90

Using **Pearson's correlation**, eliminate highly correlated features:
(R_SBC, R_SBD, R_ACT*),
(D_ACT, D_AUT*),
(F_SBC, F_ACT*),
(R_ACS*, R_SBD),
(D_AUT, D_ACT*), and
(R_SUS*, R_RUS)
over THR. |0.90|

* We dropped the red ones.

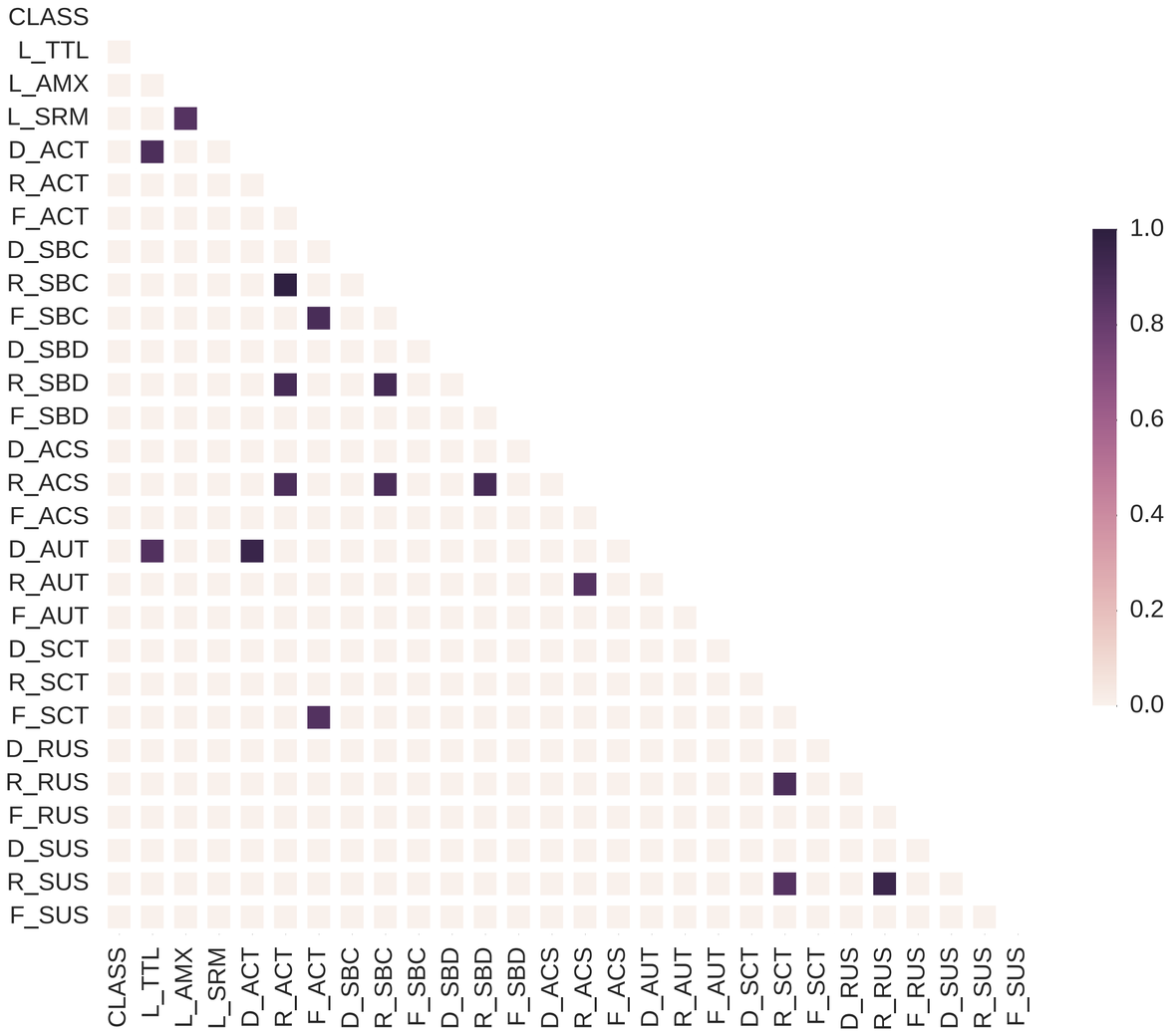


Feature Selection – C_85

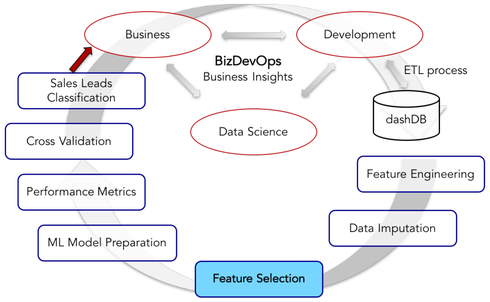


Using **Pearson's correlation**, eliminate highly correlated features:
(R_SBC, R_SBD, R_ACT*), (D_ACT, D_AUT*), (F_SBC, F_ACT*), (R_ACS*, R_SBD), (D_AUT, D_ACT*), (R_SUS*, R_RUS), (L_SRM, L_AMX*), (D_ACT*, L_TTL), (D_AUT, L_TTL), (R_AUT*, R_ACS), (F_SCT*, F_ACT), (R_ACS*, R_ACT), (R_ACS*, R_SBC), and (R_RUS*, R_SUS, R_SCT)
over THR. |0.85|

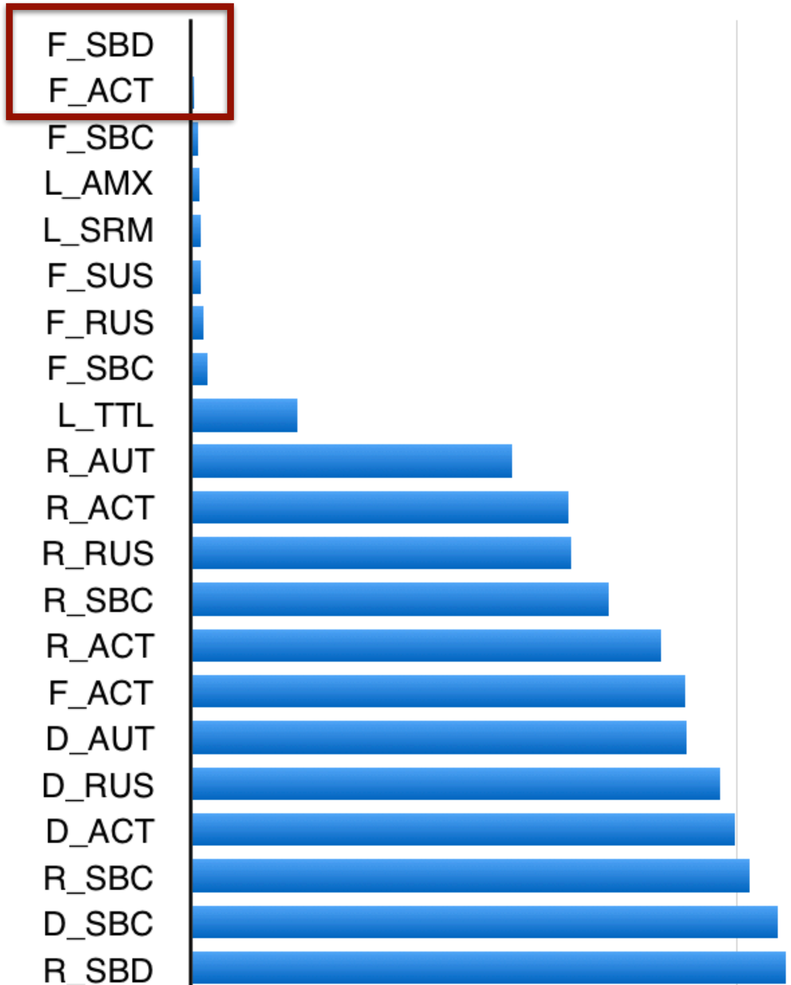
* We dropped the red ones.



Feature Selection – L_V1

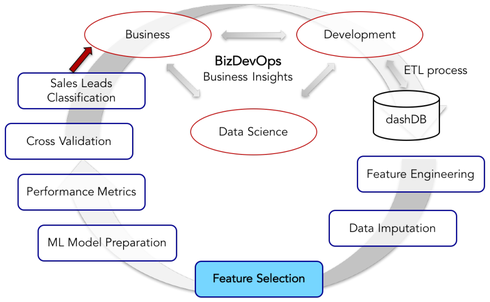


Eliminate very **low-variance** features:
F_ACT*, F_SBD*
(less than 2000)

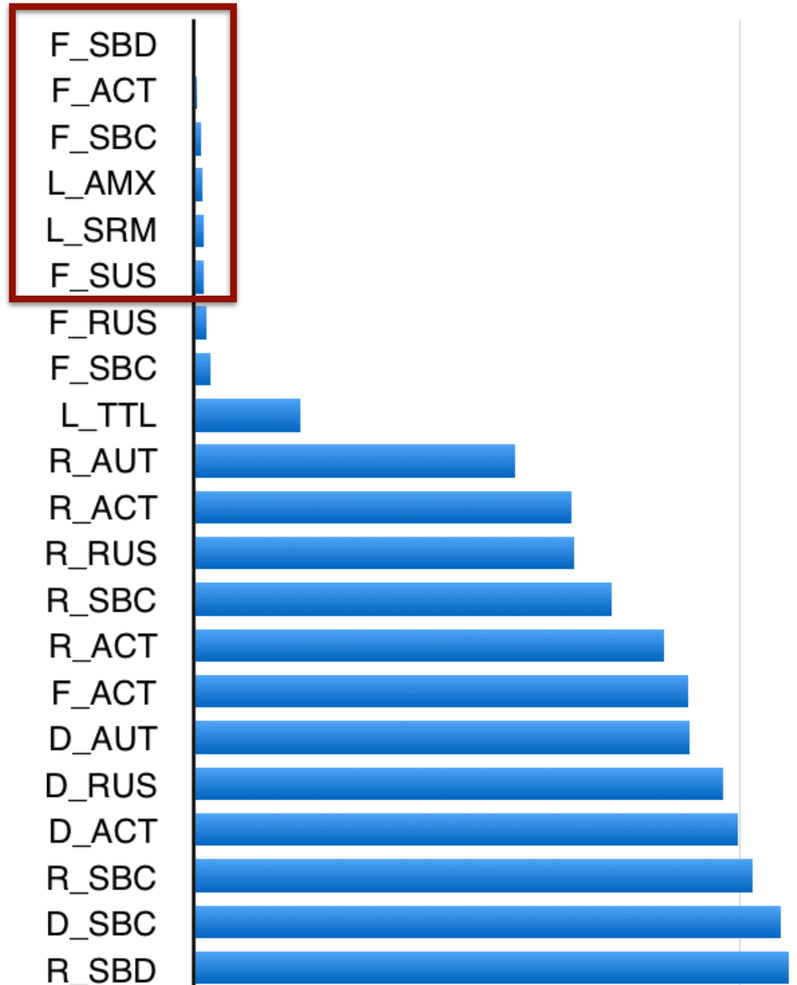


* We dropped the red ones.

Feature Selection – L_V2

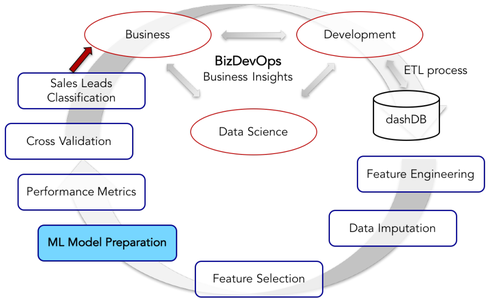


Eliminate very **low-variance** features:
F_ACT*, F_SBD*, F_SUS*, L_SRM*, L_AMX*, and F_SBC (less than 3500)



* We dropped the red ones.

Model Preparation

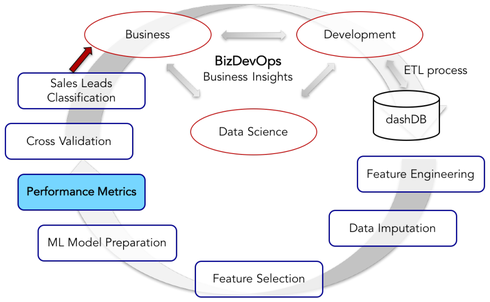


five groups of features:

ALL, C_95, C_90, C_85, L_V1, L_V2

- logistic regression (**LR**)
- k-nearest neighbor (**KNN**)
- naive Bayes (**NB**)
- decision tree (**DT**)
- random forest (**RF**)
- adaptive boosting (**AB**)
- gradient boosting (**GB**)
- weighted RF (**WRF**)
- weighted AB (**WAB**)
- weighted GB (**WGB**)

Performance metrics



On our **class-imbalance situation** where a few customers vs. the majority of non-paying customers, we have to consider:

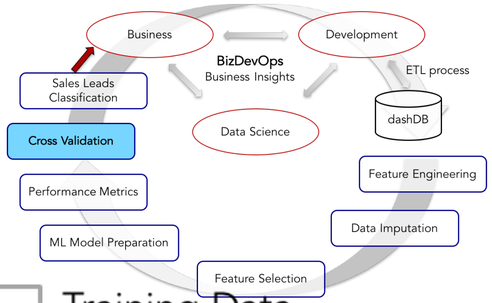
1. accuracy of positive classification:
   Precision = TP / (TP + FP)
2. accuracy of true-positive value:
   Recall = TP / (TP + FN)

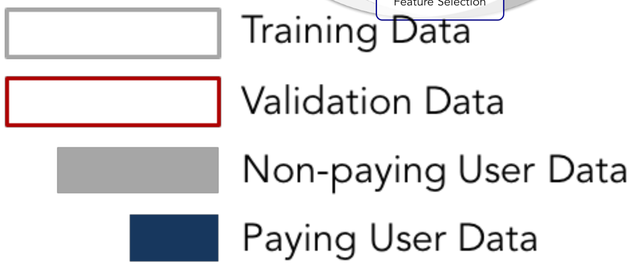
harmonic average

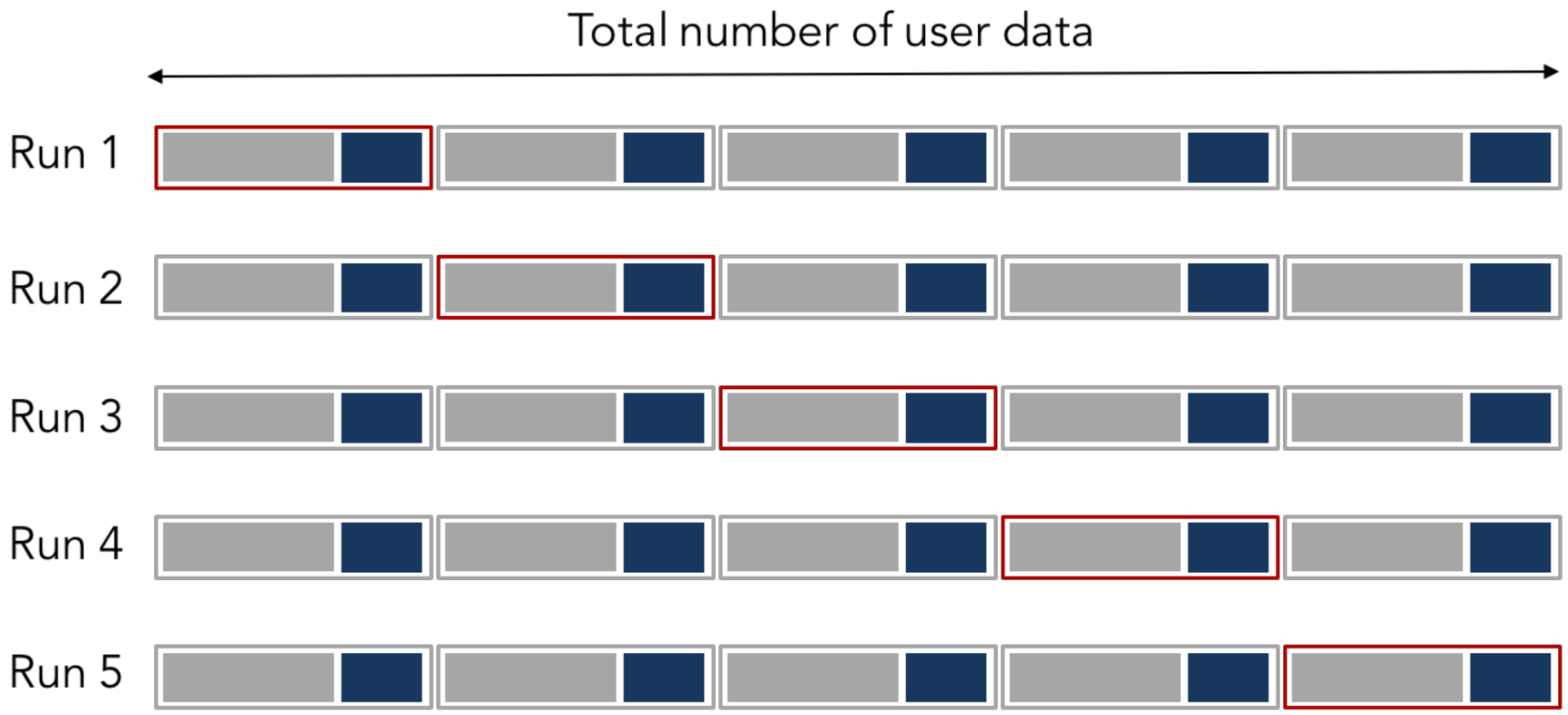
(Positive) **F1 Score**

Cross Validation

Stratified 5-fold cross validation to deal with our **class-imbalance situation**.



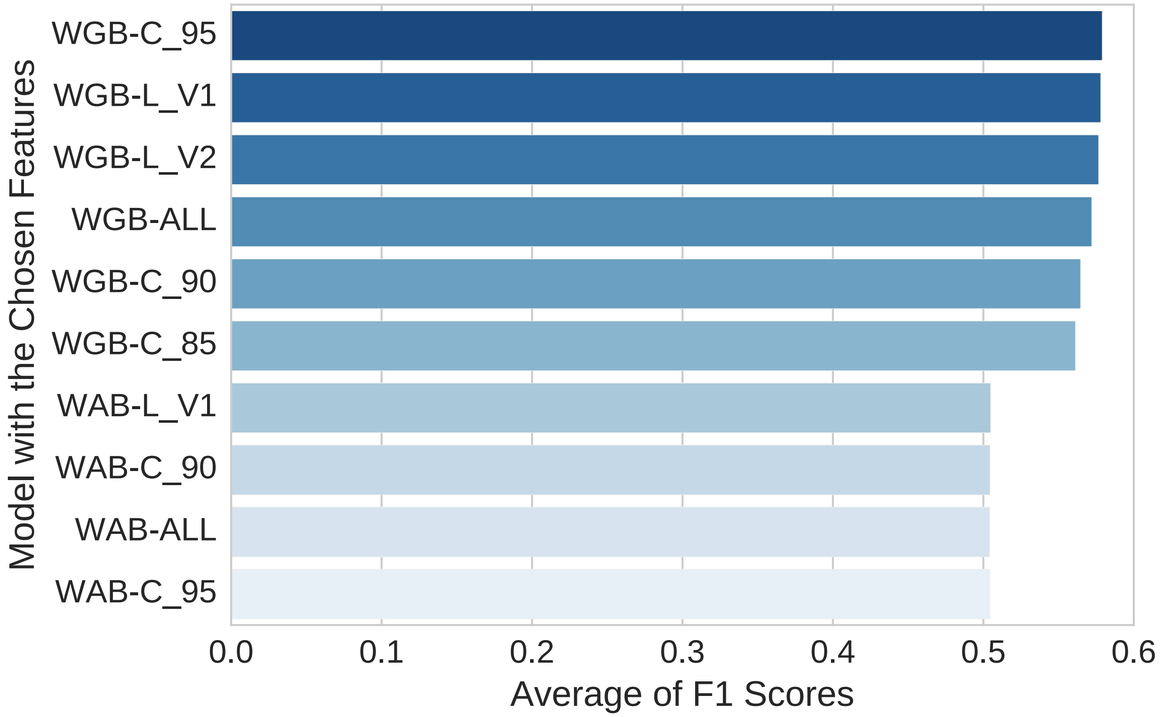




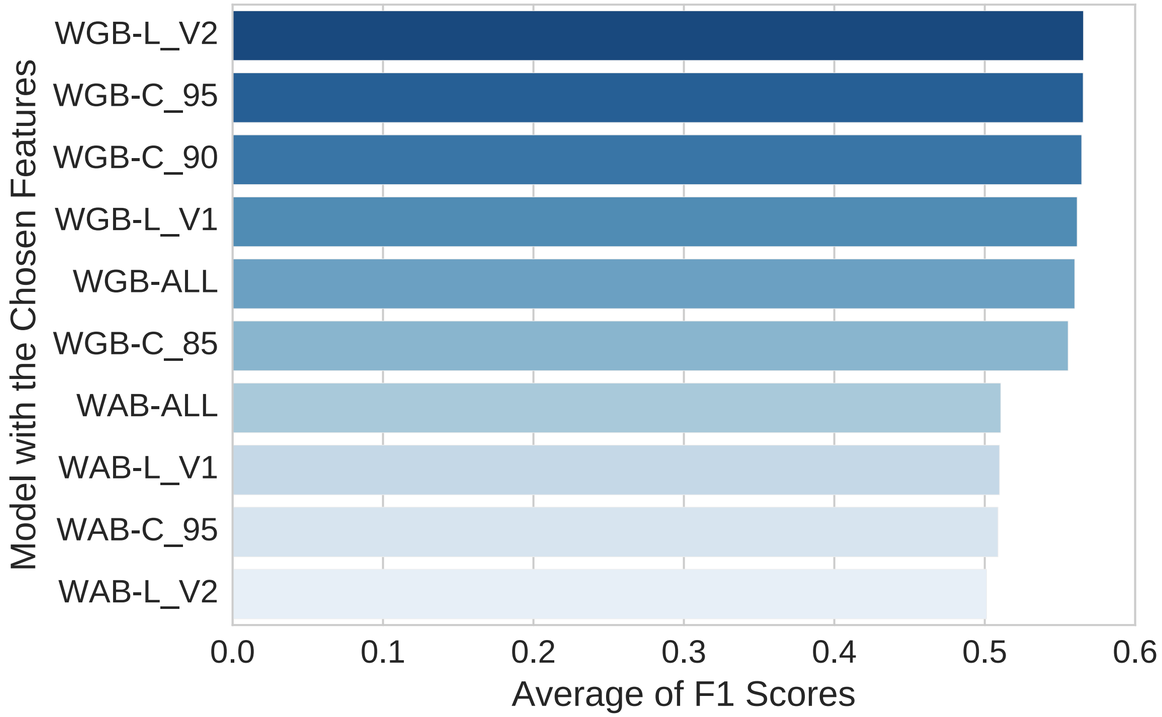
Performance Comparison (1)

Weighted Gradient Boosting (WGB) outperformed others.

June



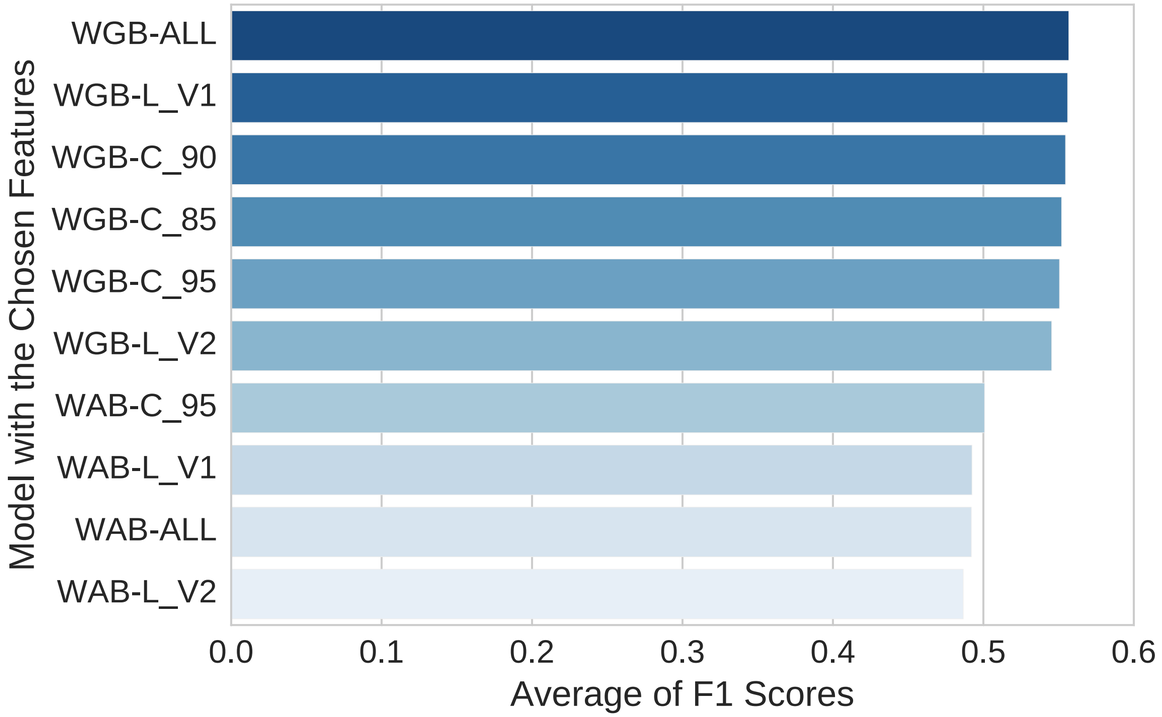
July



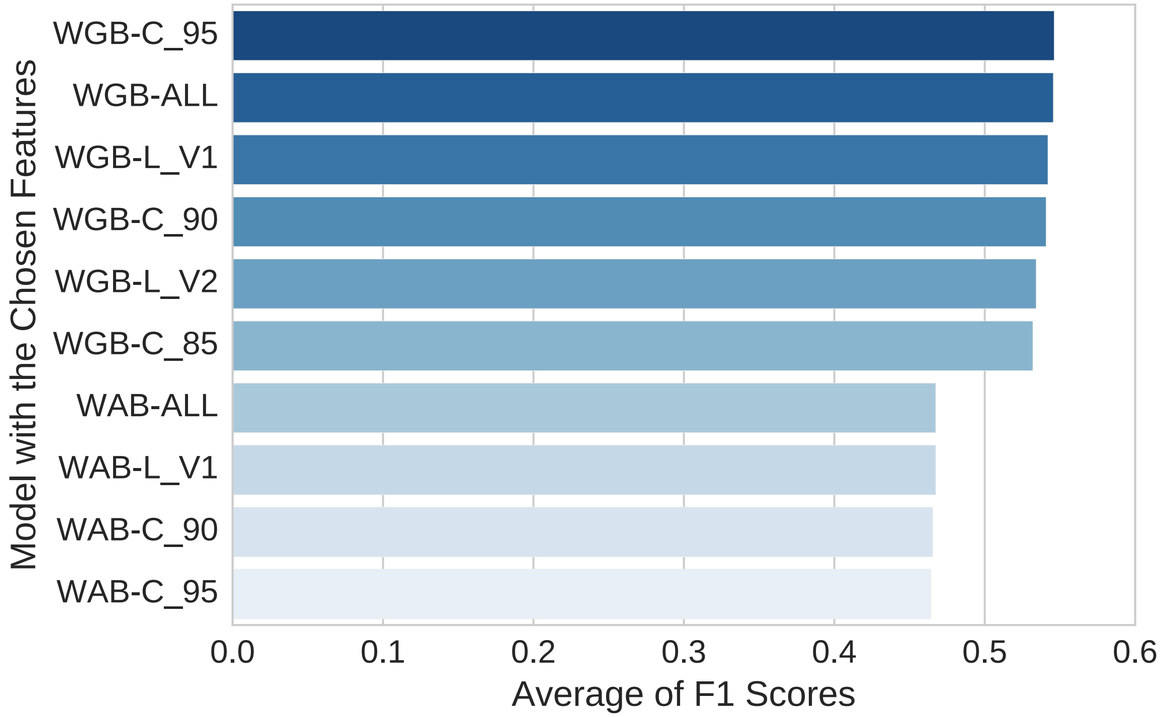
Performance Comparison (2)

Weighted Gradient Boosting (WGB) outperformed others.

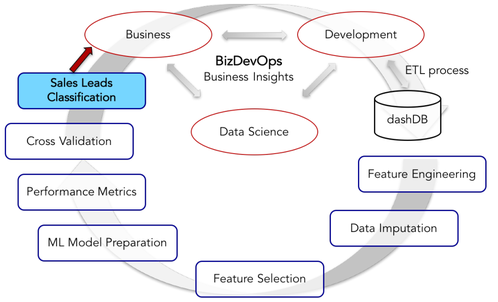
August

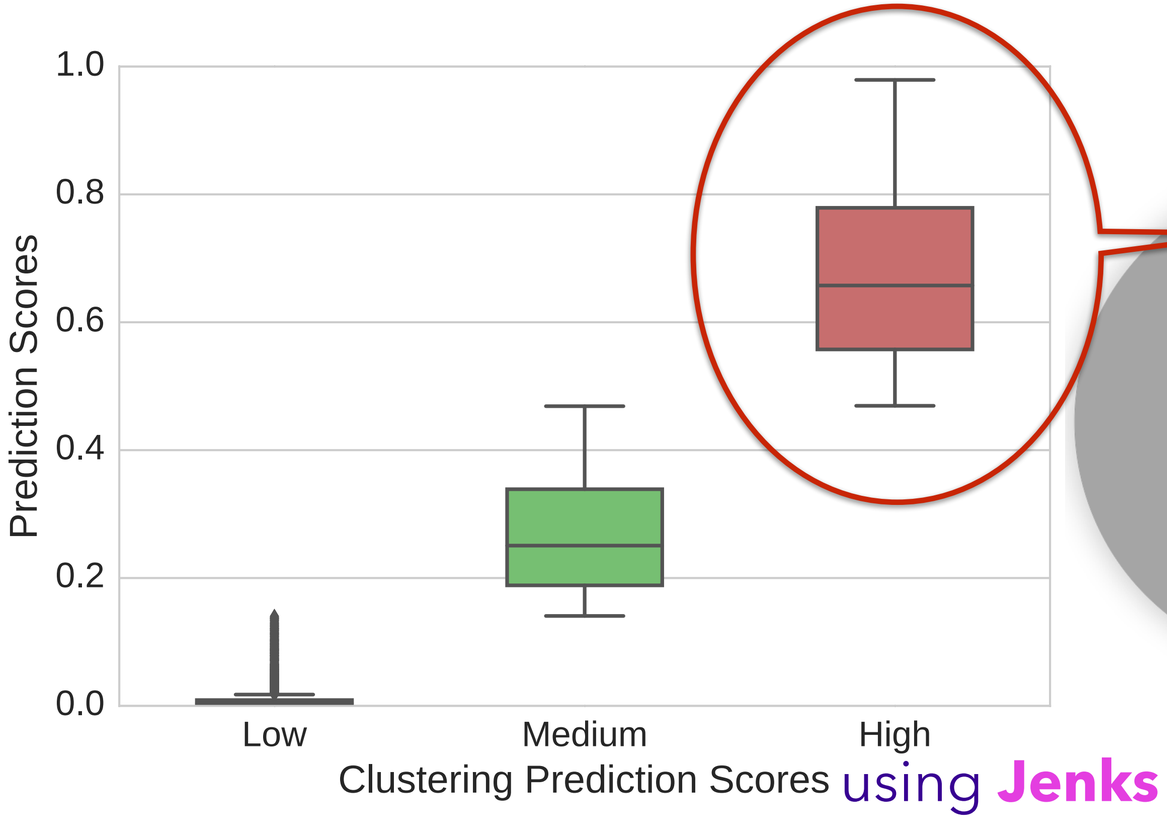


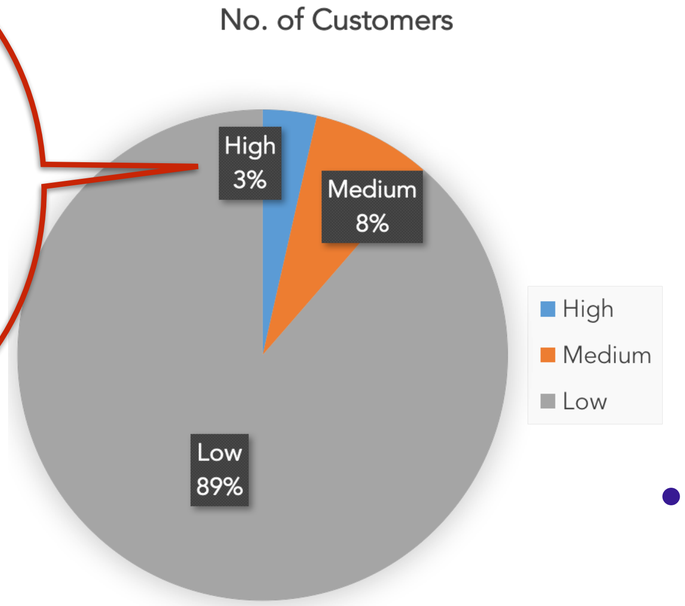
September



Sales Leads Clustering



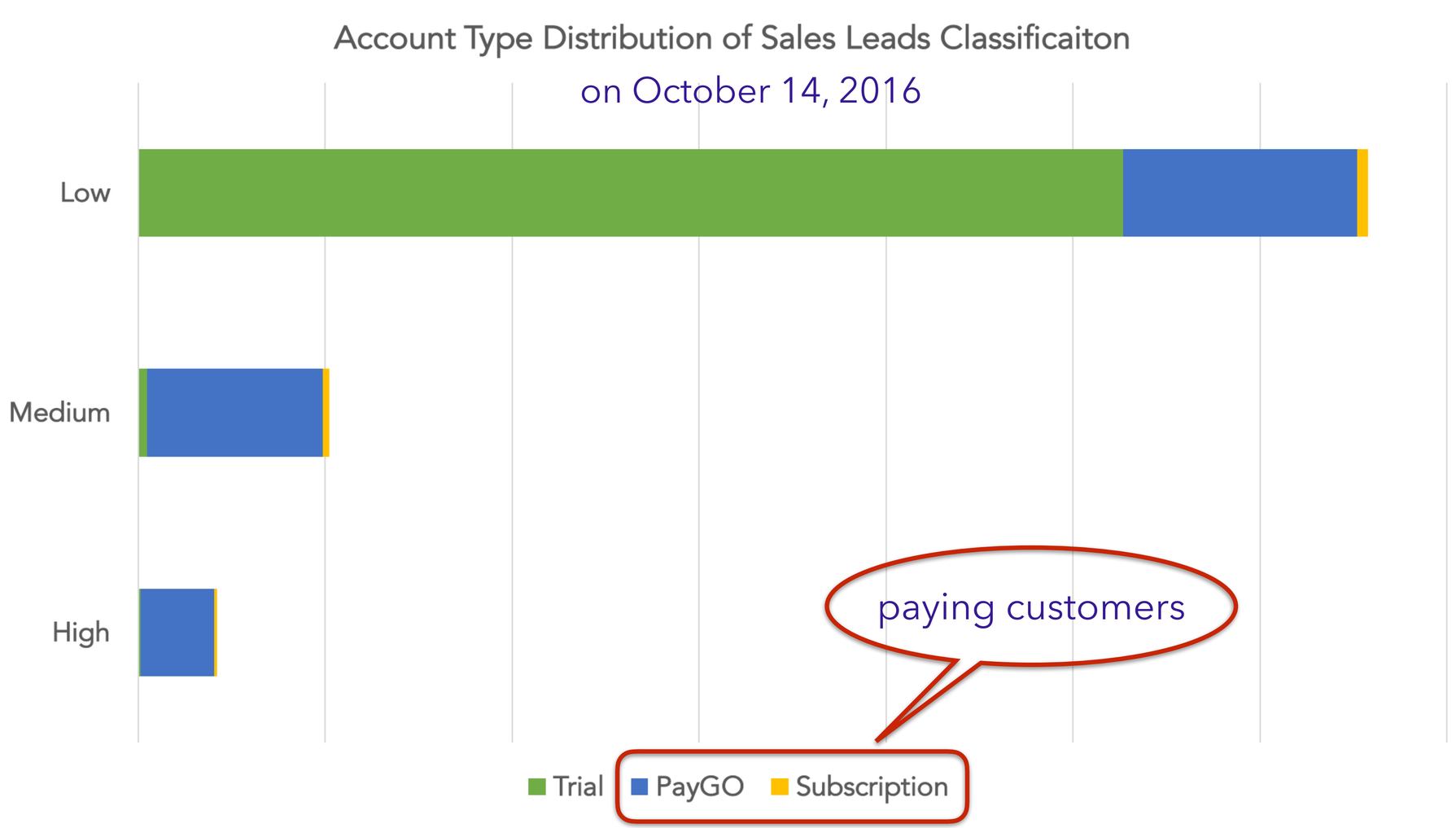




- Once we have the prediction scores from our trained model, we cluster three groups using **Jenks** algorithm.
- We deliver the **High-class** group (even 3% overall) to the Business team.

Evaluation of Sales Leads Clustering

- **Account types** in October from Sales Leads three classes in September
- In the High & Medium classes, **a few trial accounts** and the majority of paying customers
- Still necessary to handle the paying customers in the low class



To protect confidential business information, we randomly selected data for a limited period of time.

Discussion

- Proposed **RFDL** (Recency, Frequency, Duration, and Lifetime) analysis to measure customer behaviors.
- **Iterative** prediction framework widely applicable to an online or cloud business domain with a constant **flux of customer traffic**
- Effective **prioritization** of new customers, targeting the high profile customers
- Necessary to handle the actual high profile customers in the low class

Questions

Thank you!

https://github.com/csung7/ieee-dsaa2016

Acknowledgements

Thank **Damion Heredia** (VP of IBM Cloud Product Management),
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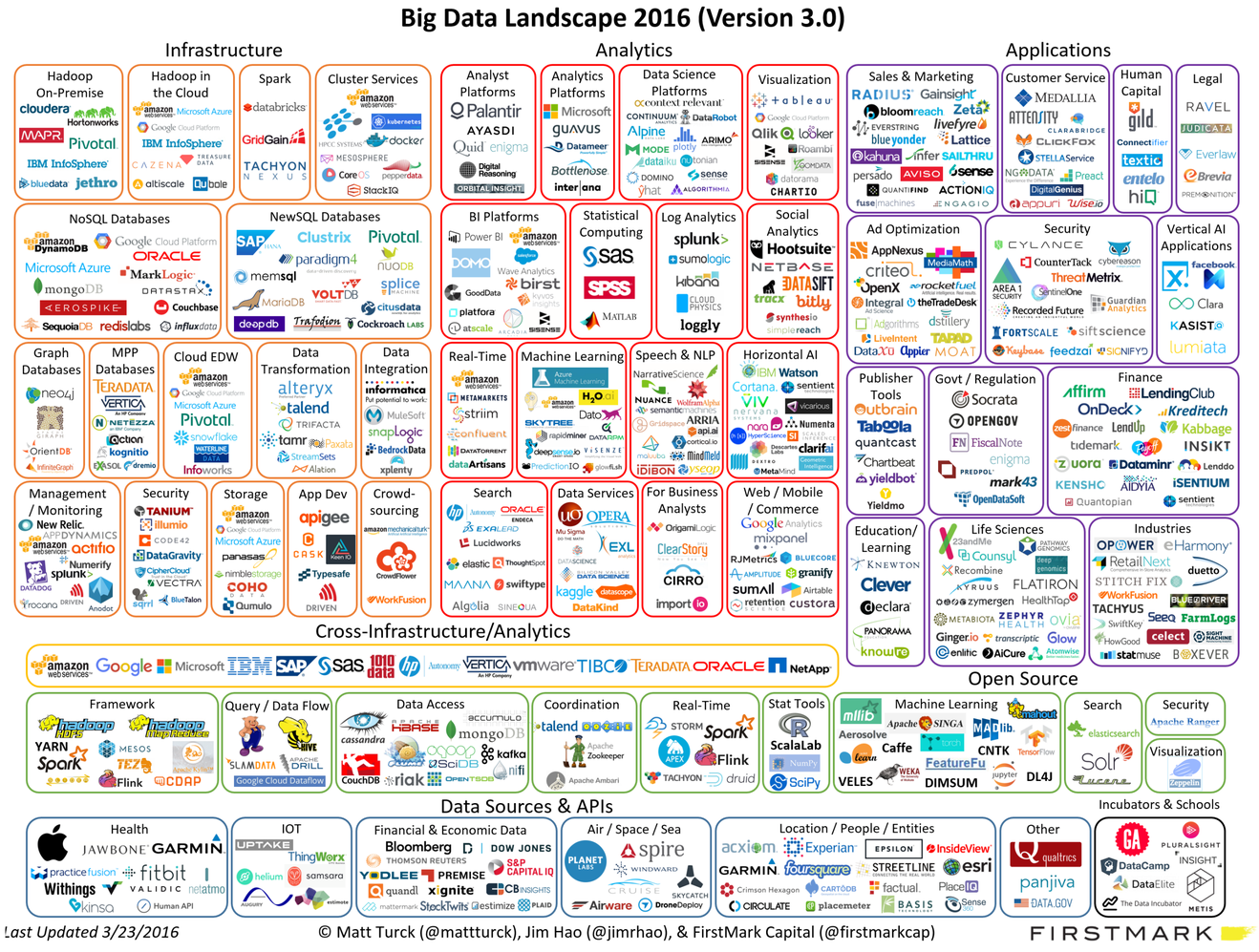
Bill Higgins (Distinguish Engineer of IBM CIO DevOps).

In addition, we would like to express our special thanks for the great collaboration to **Alexander Sobran**, **Ticard Bowser**, **Pete Marshall**, and **Pete Parente**.

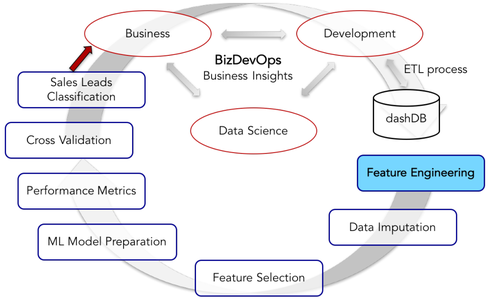
Big Data Landscape

- Big Data Landscape in 2016
- For interest of **Big Data** at fever pitch, big data companies standing out
- A variety of applications on **across cloud platforms** within the enterprise



source: http://mattturck.com/2016/02/01/big-data-landscape/

Feature Code Description



RFDL	Features (Abbr.)	Descriptions
R/F/D	{R/F/D}_ACT	Recency, Frequency, or Duration of application creation.
	{R/F/D}_ACS	Recency, Frequency, or Duration of application crash.
	{R/F/D}_AUT	Recency, Frequency, or Duration of application update.
	{R/F/D}_SCT	Recency, Frequency, or Duration of service creation.
	{R/F/D}_SBC	Recency, Frequency, or Duration of service binding creation.
	{R/F/D}_SBD	Recency, Frequency, or Duration of service binding deletion.
	{R/F/D}_SUS	Recency, Frequency, or Duration of service usage.
	{R/F/D}_RUS	Recency, Frequency, or Duration of runtime usage.
L	L_TTL	Lifetime of customer accounts.
	L_AMX	Lifetime of applications.
	L_SRM	Lifetime of services.
	CLASS	Labels for paying and non-paying customers.