



## ML Infra at an Early-Stage Feature Service



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# Big challenges require big minds -

We're interested in the rising stars with a worldly perspective, a deep interest in financial technology, and an appetite for growth.

See current openings

## Our mission is to deliver world-class financial services to the mobile generation.



#### From Install to Approval in Minutes

#### 1 ANSV

#### ANSWER 3 QUESTIONS TO REGISTER

KYC checks with external APIs, mobile data mined and analysed.

2

ELIGIBLE LOAN OFFERS ARE DISPLAYED

Credit score calculated in seconds.



Repayment schedule set and monitored.





#### How Branch works behind the scenes



We collect

- Text messages
- Installed apps
- Contact lists
- In-app events

We extract

- Bank balance
- Number of contacts
- Read the FAQ
- Installed Facebook app

We predict probability of repayment



#### How do I build ML into my product?

### Big Firms Can Build Custom ML Infrastructure





#### Can the rest of us do machine learning?

We too can build infrastructure but must be strategic.

Build a Feature Service!

#### What does a feature service do for me?

- Faster development of new features
- Reduce bugs with consistent feature definitions
- Speed-up slow feature calculations
- Easy feature discovery and sharing



#### Where do you start?



#### You want to start basic



#### You will gradually mature your ML



## The basics will only get you so far

Model Training AUC



#### What do you focus on beyond the basics?



#### We needed to improve our features

Our data sources were in ok shape but

- Differences in features between dev, training and production lead to bugs
- Inconsistent feature definitions lead to bugs
- Feature creation was a training bottleneck



## We invested in infrastructure to improve features.

#### We decided to build a Feature Service



#### What is a Feature Service?

A Feature Service computes a feature vector for a specific object at a specific time.





#### Features are computed relative to a timestamp





#### Features are accessed by a simple API



pid = primary id, like user id

#### Why build a custom solution?



### What are we building?



- Server infrastructure
- Cache infrastructure
- A Python framework

#### Data source dependencies were messy



#### We abstracted complicated data sources



Read \_\_\_\_\_



#### Features were being created all over the place



Write Read

#### Every step of ML shares consistent features





#### New models were recreating features



Write Read

#### ML models now share the same features



#### The Feature Service server helps a lot

- Abstracted data sources
- Shared features
- Consistent features

Now onto storage....



#### Features were computed once and forgotten



#### We built feature storage and caching



#### We sped up training with a cache





#### Feature storage helps too

- Remove recomputation of features
- Enable analytics and monitoring
- Increase training speed

#### We built with simple components



#### Simple infrastructure solved many problems



### How do we actually generate features?



Write	
Read	

#### We built a framework

Features are composed of

- One or more *Extractors* which pull data from a Raw Data Source
- Many *Transformers* which convert the data into a numeric or categorical features





#### Extractors and Transformers are shared





#### Framework example

Everything is built on base classes with automated testing

Features are built on versioned extracts and transforms

As flexible as Python

Chain of transformations

Custom one-off \_\_\_\_\_\_

from framework.feature import Feature
from framework.transform import Transform

from extract.sms.v0\_3 import SmsExtract

from transform.filters.filter\_row\_values.v0\_1 import FilterRowValues
from transform.mappers.pluck\_regex\_value.v0\_2 import PluckRegexValue
from transform.column\_utilities.select\_column.v0\_1 import SelectColumn
from transform.column\_utilities.rename\_column.v0\_1 import RenameColumn

class AverageBankBalance(Feature):

```
BANK_ADDRESSES = [
    "MPESA",
    "NIC",
    "CHASE",
]

def __init__(self, **kwargs):
    pipeline = [
    SmsExtract(),
    FilterRowValues(column="address", values=self.BANK_ADDRESSES),
    PluckRegexValue(column="message", pattern=r"KSH(\d+)"),
    SelectColumn(column="message"),
    RenameColumn(from="message"),
    RenameColumn(from="message", to="average_bank_balance"),
    WeightedAverage(column="average_bank_balance"),
    ]

    super(). init (pipeline=pipeline, **kwargs)
```

#### Feature versions support new models



#### The framework makes development easy

- Feature definitions are consistent
- New features are easy to build from shared components
- Versioning allows backwards compatibility and bug fixes

#### The Feature Service solves many problems



#### Should I build a Feature Service?

- Is feature quality a problem for you?
- Are your data sources complex and varied?
- Do you want to support multiple models?
- Are your features difficult to compute?

## We're benefitting from our Feature Service

- Feature generation time reduced!
- Fixed a lot of bugs by using the framework!
- New models without remaking features!
- New data scientists can contribute within a week of joining!
- And our model performance has improved!

#### What should I take away?

- You don't have to be a big company to use ML infrastructure
- But your resources are limited so be strategic
- And invest in a Feature Service!
- Stay informed because the landscape changes fast
  - Airbnb Big Head may be open sourced soon

**The Team** Dennis Van Der Staay **Dave Bernthal Ting Ting Liu** Nick Handel **Spencer Barton** 



## **Thank You!**

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## Appendix



## Who else is talking about Feature Services?

- Nick Handel delivering an earlier version of this presentation
- Varant Zanoyan, Zipline at Airbnb
- Uber's Michelangelo