ML in production

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Agenda

- About production
- Actuality of prediction
- From notebook to microservice
- Scale up your solution
- Monitoring & automatic problem solving
- Conclusion

https://clck.ru/FATUR

Main problems of production

Time

- Actuality of prediction

Data

- Inconstancy of data
- Difference between train / evaluation sets

Model

- Model sharing
- Model maintaining: regularly predict / re-train

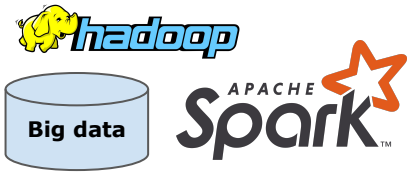
24/7 without engineer

- Automatic monitoring
- Automatic problem solving

Actuality of prediction

Offline prediction (~3+ hour)

Churn prediction, User-Item recommendations



Actuality of prediction

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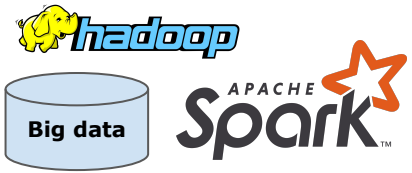
Churn prediction, User-Item recommendations



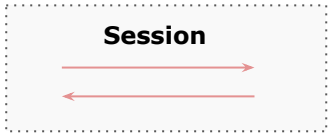
Online prediction (~5 minute)
Classify photo, Rate announcement ads

Actuality of prediction

Offline prediction (~3+ hour)
Churn prediction, User-Item recommendations

Online prediction (~5 minute)
Classify photo, Rate announcement ads

Realtime prediction (~300ms)
Search results, Ads recommendations
{Strong timeout SLA}



Inconstancy of data

Schema validation

Format validation using XML/Json schema

Inconstancy of data

Schema validation

Format validation using XML/Json schema

Data validation

Range validation. Test using hypotheses

Inconstancy of data

Schema validation

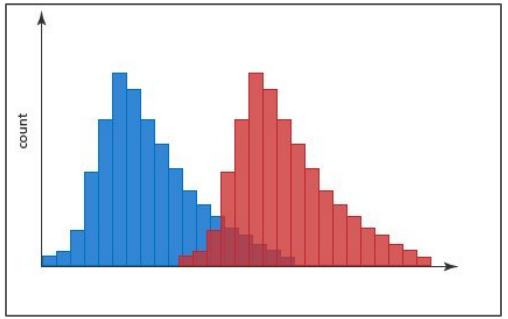
Format validation using XML/Json schema

Data validation

Range validation. Test using hypotheses

Distribution validation

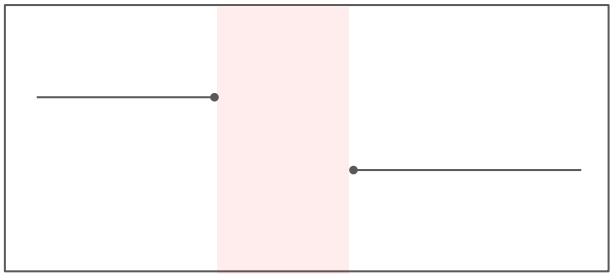
Descriptive statistics



Difference between train / evaluation sets

Train / Evaluation Time Gap

Time between train set and evaluation set



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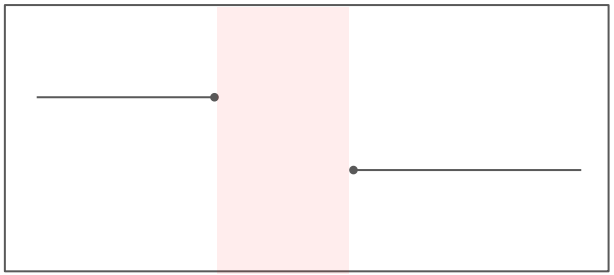
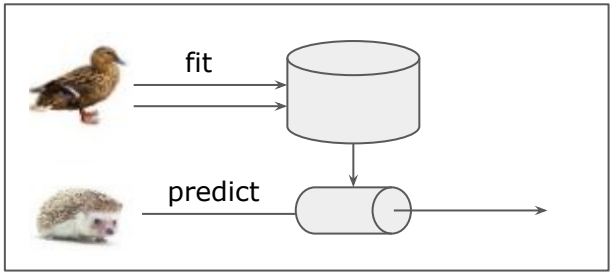


Feature extraction pipeline

Pipelines must be the same



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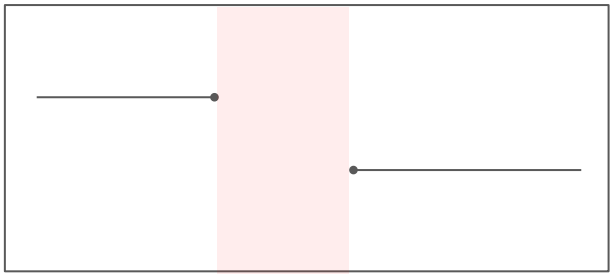

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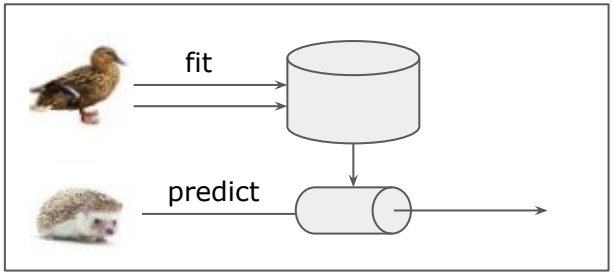
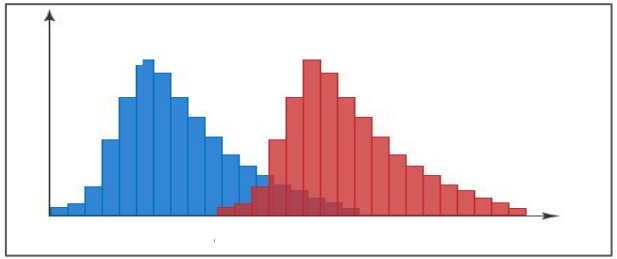


Features distribution
Features distribution should be the same



How to share models

- solution.ipynb
- requirements.txt

- solution.py
- test_solution.py
- requirements.txt
- Dockerfile

Frozen dependencies

Python packages, System libraries

Tests

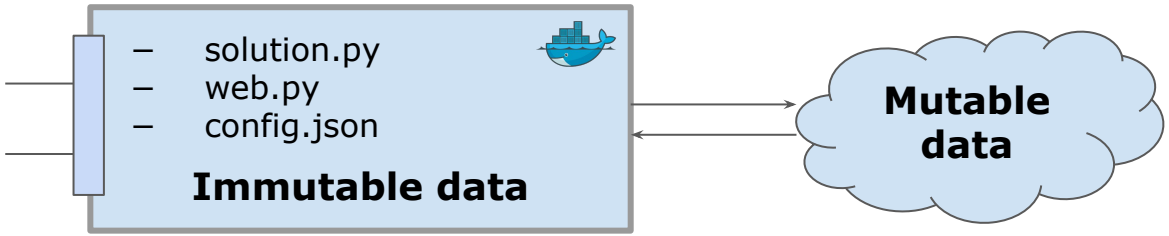
Unit tests, Integration tests, Exploration tests (hypothesis), Tests with data

Public interface

Expose your interface using REST (Flask, Tornado), describe it in Swagger

Stateless service

Stateless service



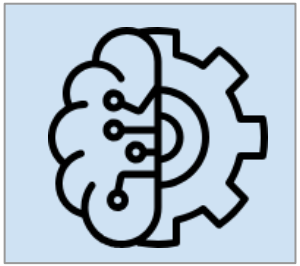
Extract state from service
Docker is an immutable container, extract the state outside

Public interface
Allow external connection only through public interfaces

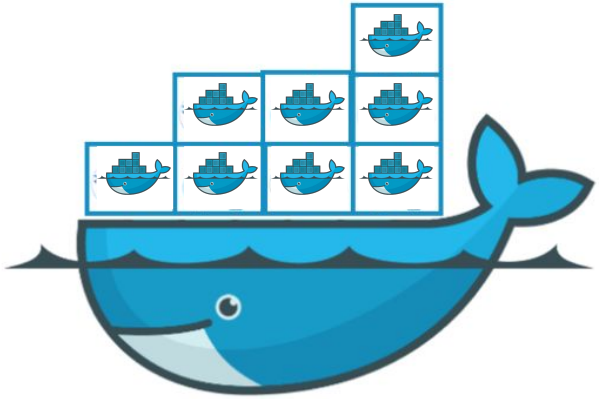
Freeze service state
Save all dependencies and sub-dependencies

Scale up your service
Stateless allows us to linearly scale our solution

Scaling up using orchestration



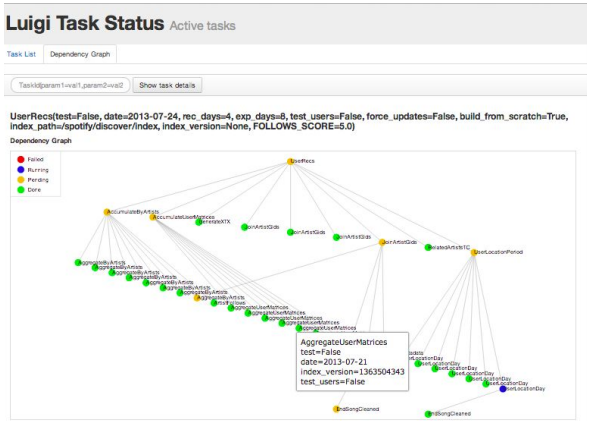
From pets to cattle



Regular offline prediction

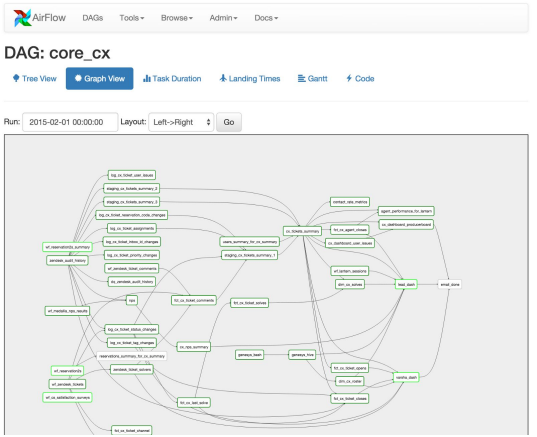
Luigi by Spotify

- Data pipeline framework
- More stable
- Scheduler is not included

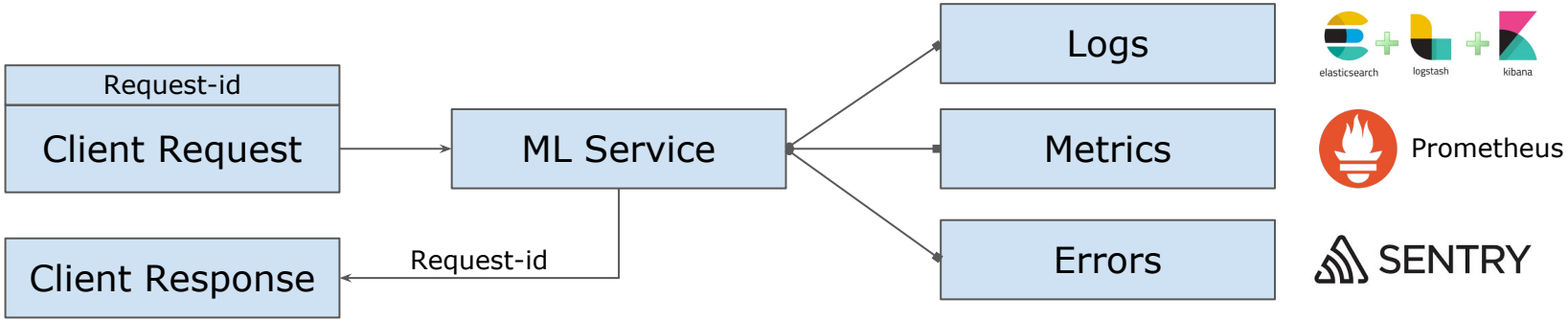


Airflow by airbnb

- Data pipeline framework
- More flexible
- More testable
- Pretty dashboard



Monitoring & automatic problem solving



Save your history

Use Logs, Metrics, Errors saving, Tracing for problem capturing and detection

Visualize your data through dashboards

Explicit is better than implicit. Visualize your key indicators

Graceful degradation.

Try to solve your problems automatically using spare models

Conclusion

- Check your inputs
- Containerize your solution
- Use Microservices Architecture
- Monitoring tools is your best friends
- Solve your problems automatically