Distributed C++-Python embedding for fast predictions and fast prototyping

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Banner Display Advertising at OLA Mobile

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1. User clicks on *generic banner ad*

2. Ad request sent with user profile
   device, OS, provider, browser, date, country code, etc.
3. Feature extraction from user profile
   Time localization, Country Code Conversion → OneHotEncoding
4. Predict most suitable ad campaign and landing page

5. Redirect user to landing page

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200 ms

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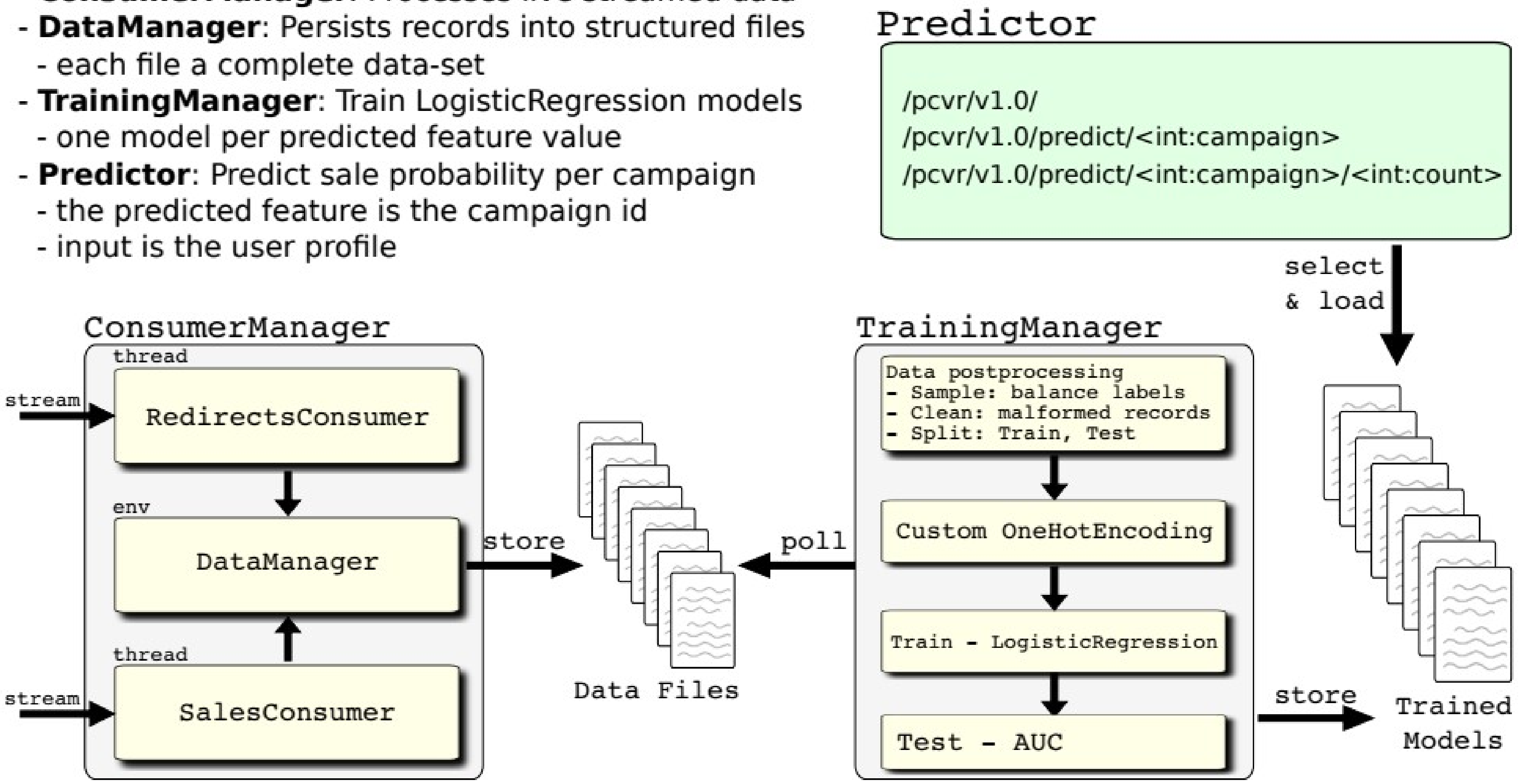
Ad Campaign classification

- 1 year of research using SciKit Learn, started in 2016
  - Uses Logistic Regression classifiers
  - Extensive tuning based on sklearn implementation specifics
- Extensive feature engineering
  - Dirty, unstructured, frequently changing data
  - Data patterns do not imply correlations
- Classification based on a boolean label: Sale, not Sale
  - Highly unbalanced datasets:
    - Some got 1 sale every 1M clicks
    - Some got 1 sale every 1K clicks
    - Achieved consistent accuracy above 90%

Online Continuous Training Service

- **ConsumerManager**: Processes live streamed data
- **DataManager**: Persists records into structured files
  - each file a complete data-set
- **TrainingManager**: Train LogisticRegression models
  - one model per predicted feature value
- **Predictor**: Predict sale probability per campaign
  - the predicted feature is the campaign id
  - input is the user profile



Predictor

- Python based implementation
  - REST server
  - Loads classifiers from disk
  - Per request, predicts with every available classifier

  - 5000 active campaigns on average, thus 5000 classifiers!
  - The 200ms deadline still applies

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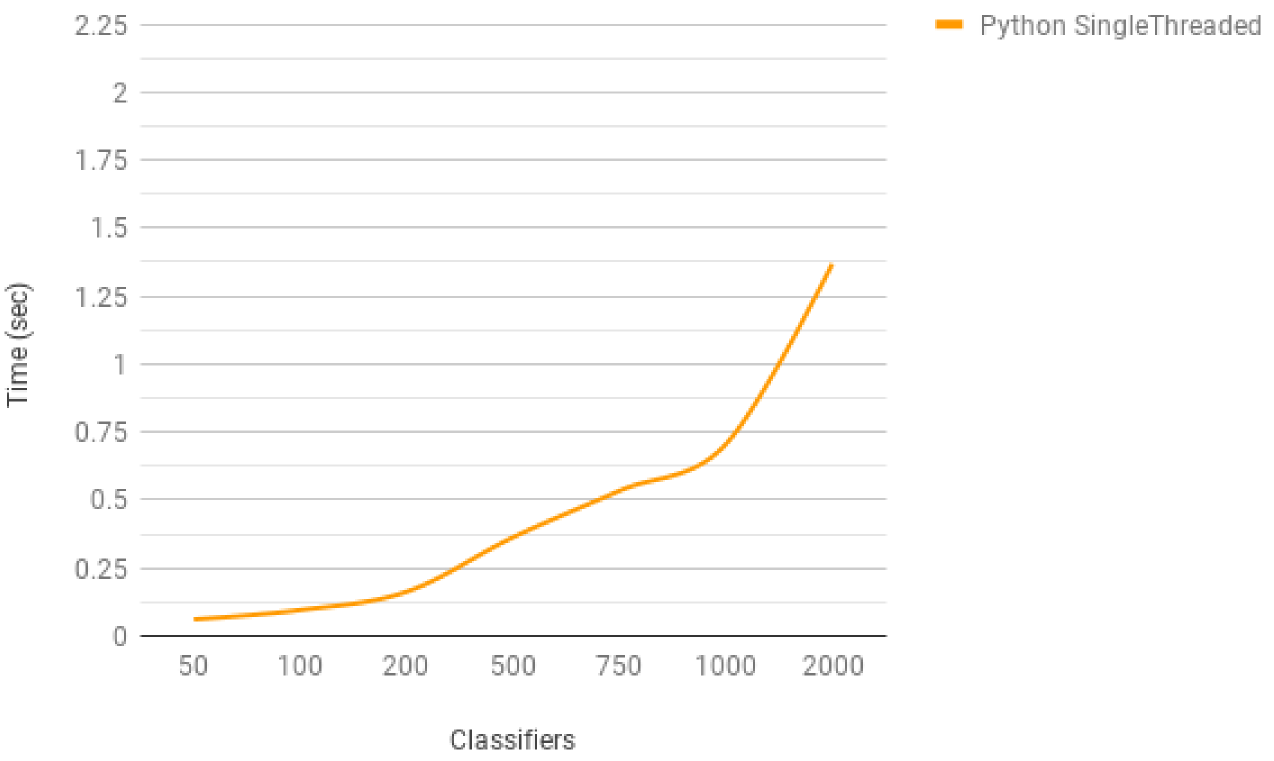
  - To obey deadline we need **77.5** hardware threads and no conflicts

Python version performance



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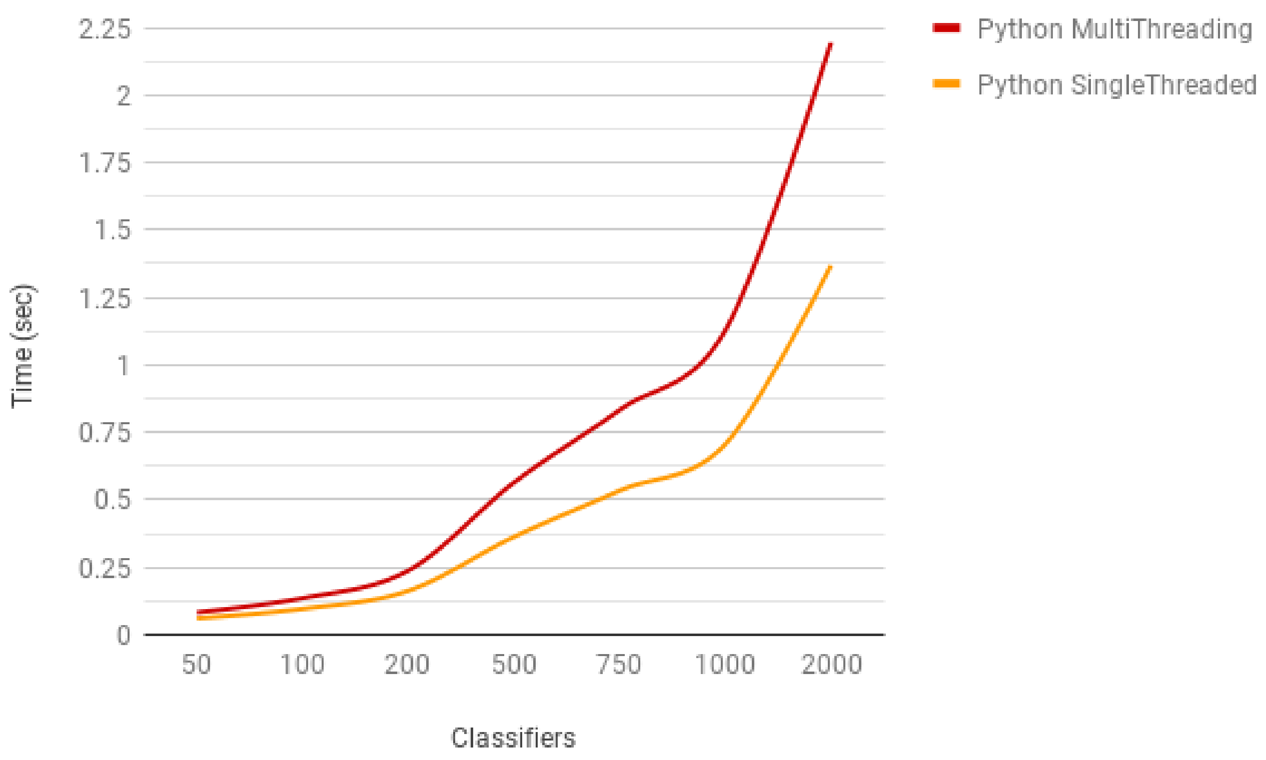

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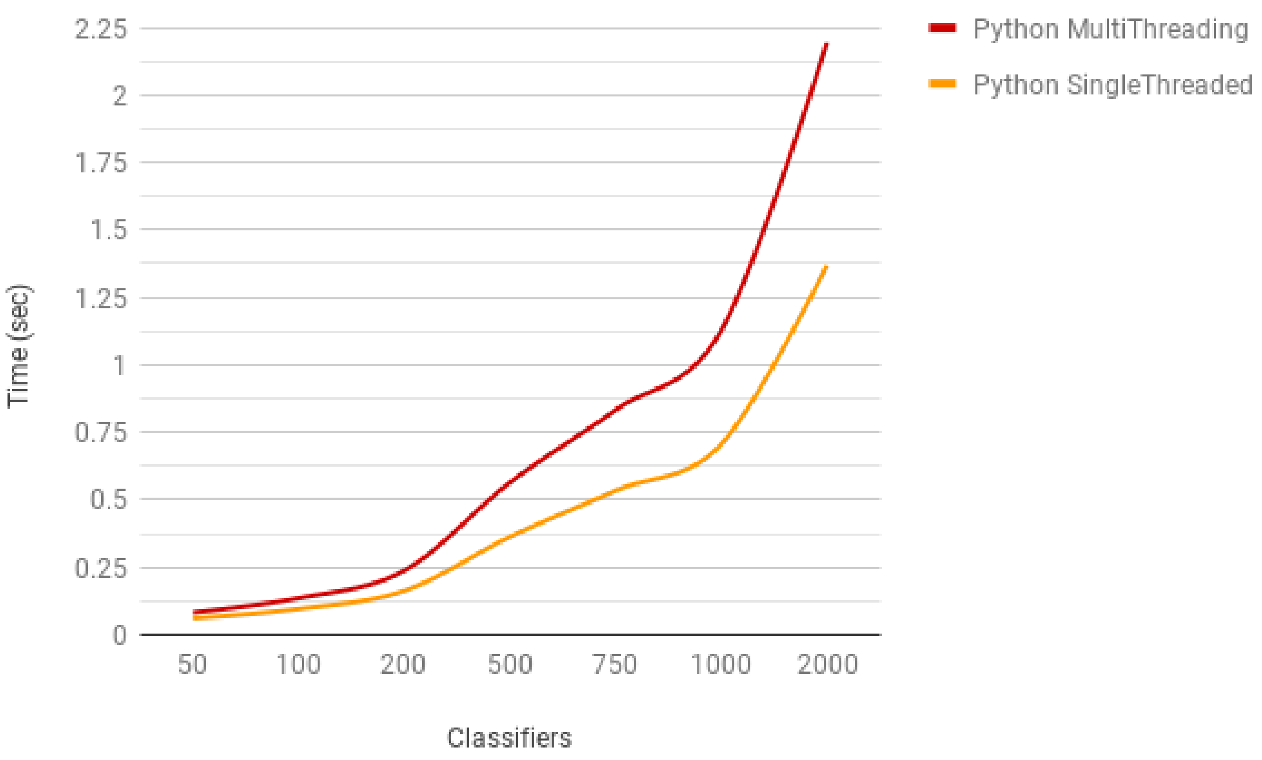

- **Python GIL: Concurrency does not translate to parallelism**

C++ to the rescue

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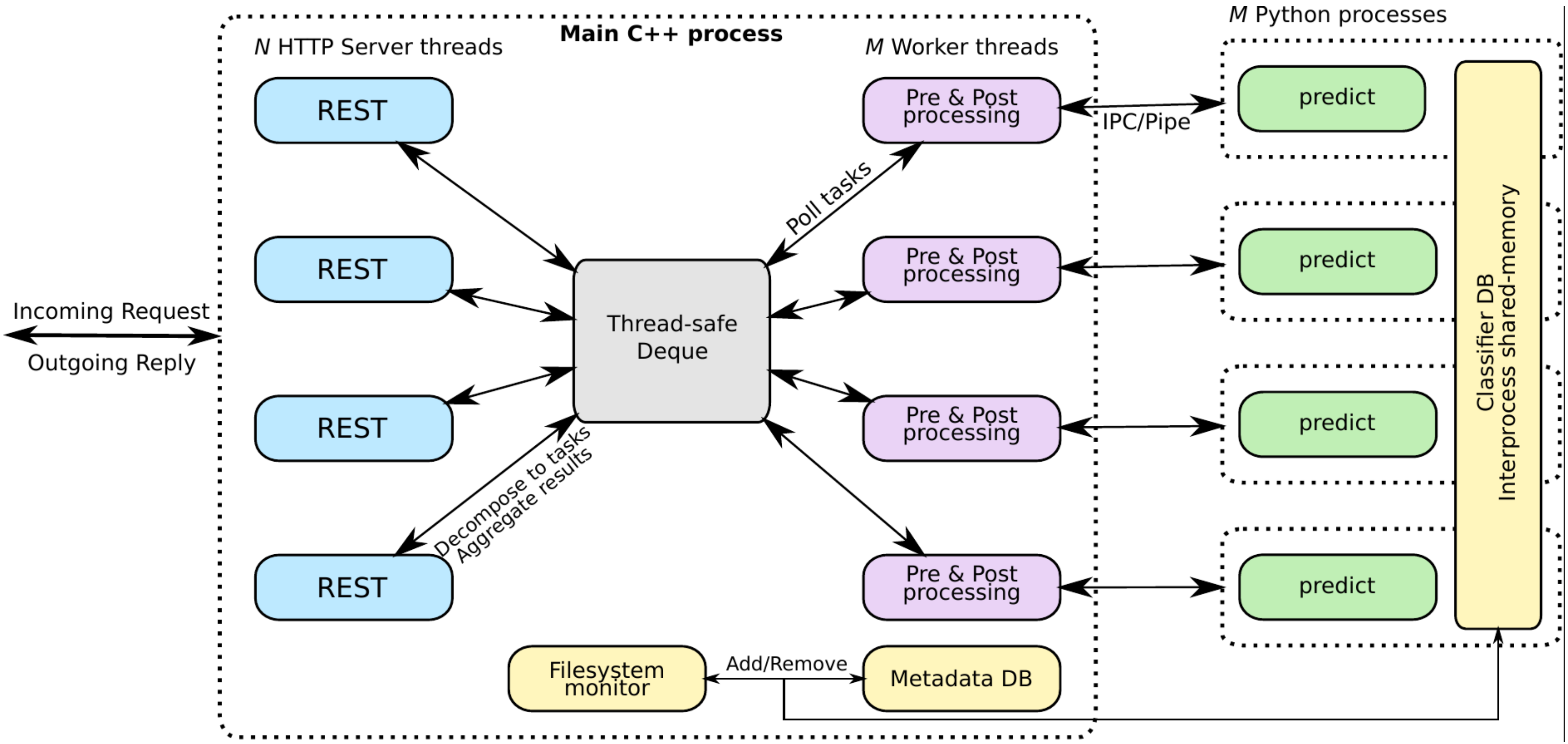
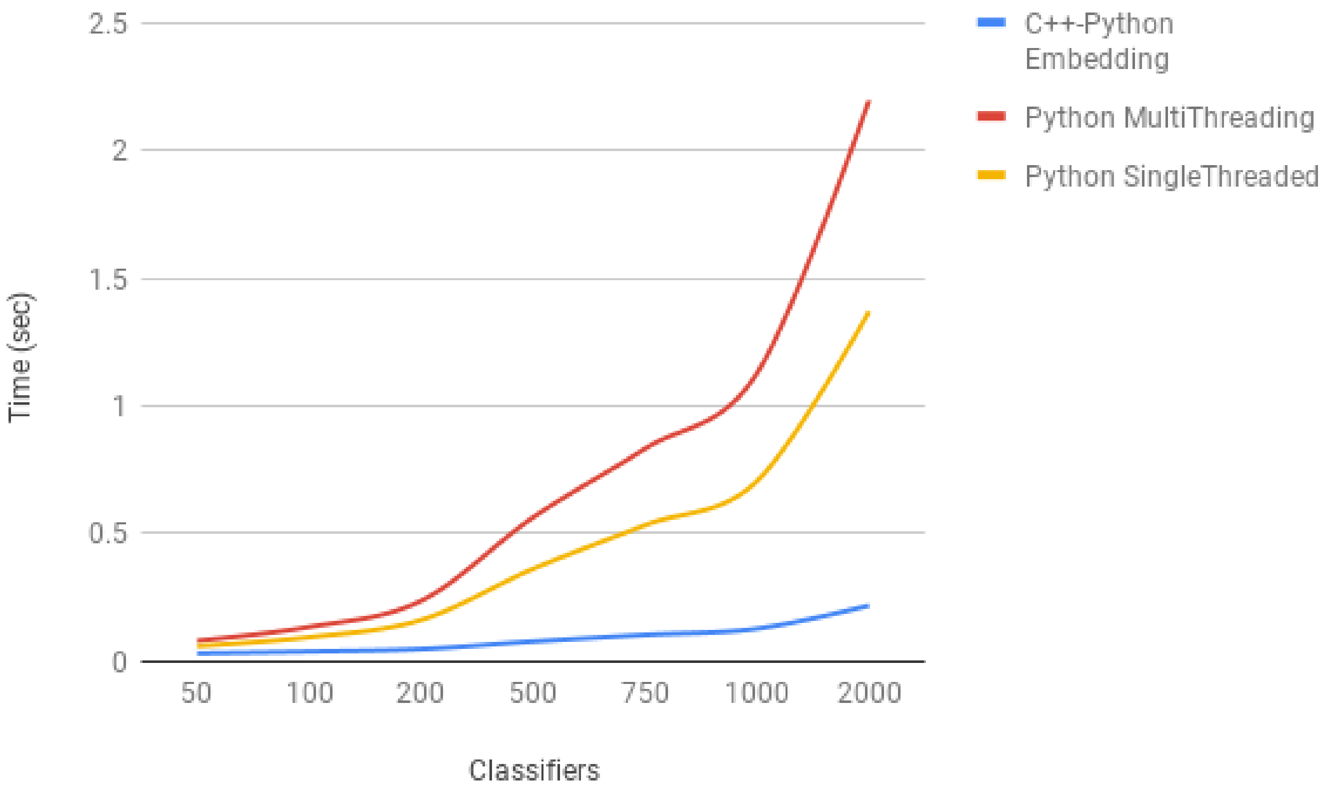
- Embed Python into C++
  - Have C++ handle all data intensive processing
    - Faster and fine grained memory management
    - Lighter data structures
    - Much faster computation execution
    - True massive parallelism
  - Execute predictions in Python
    - 0.8ms per classifier
    - Implement Python multi-processing: no GIL
    - **No need to change ML framework**
    - **No need to change the trainer**

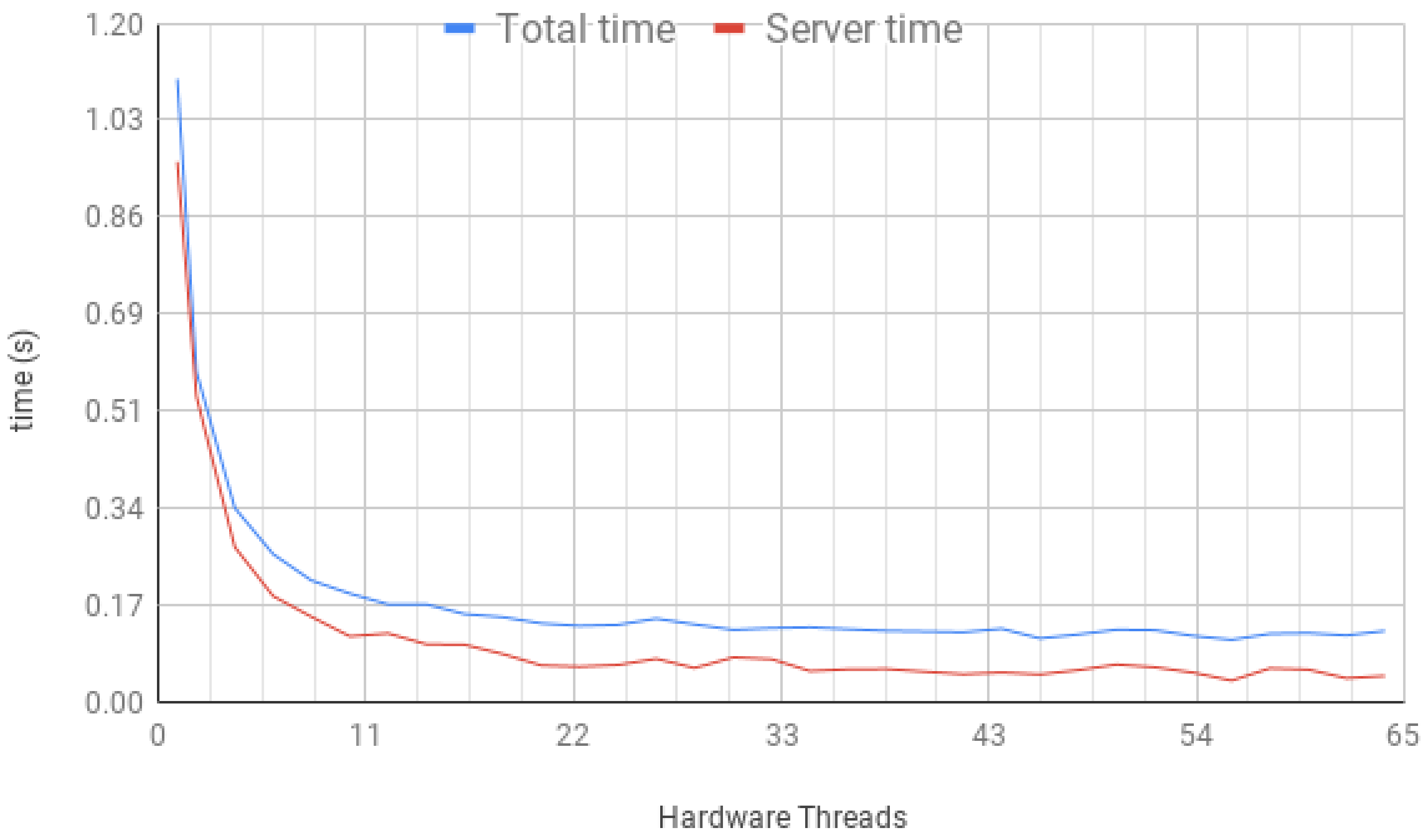
C++ to the rescue



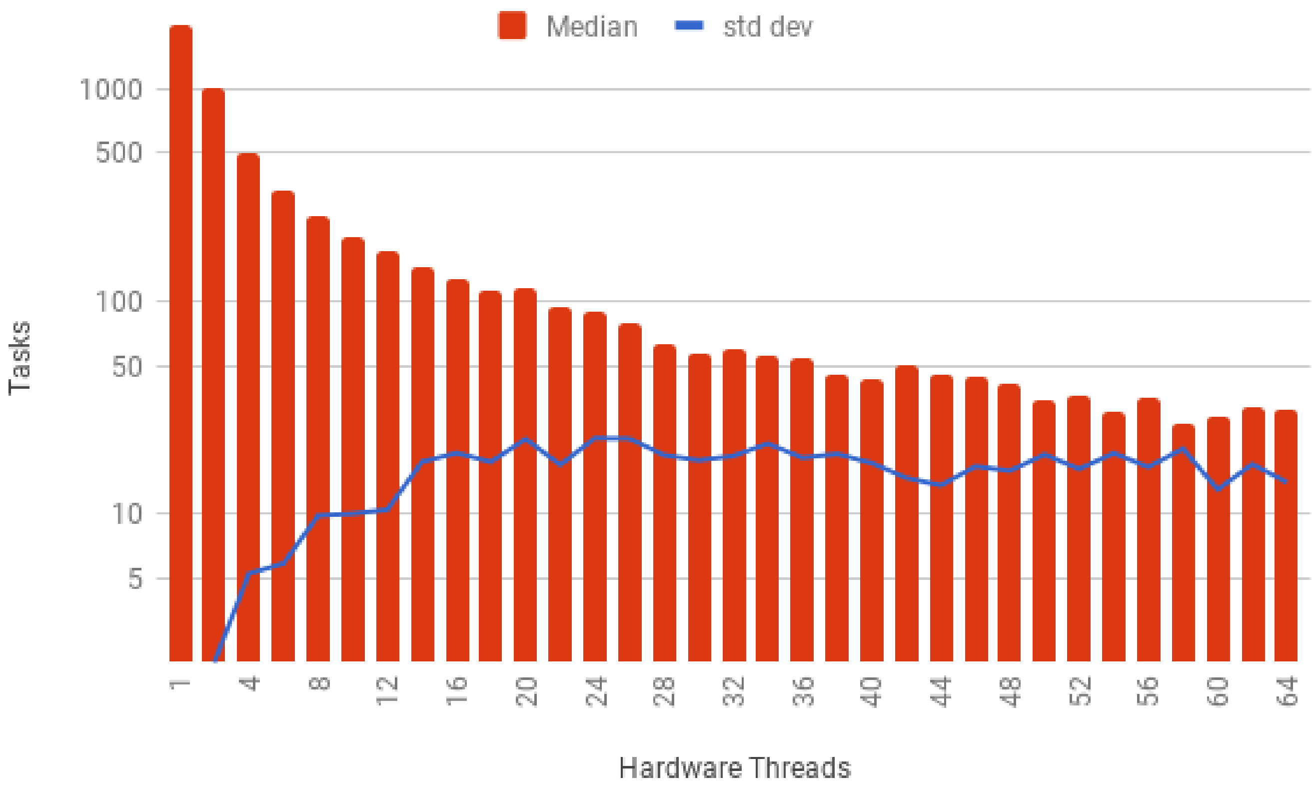
C++-Python Performance



C++-Python Scalability, 2000 classifiers



C++-Python Worker Utilization



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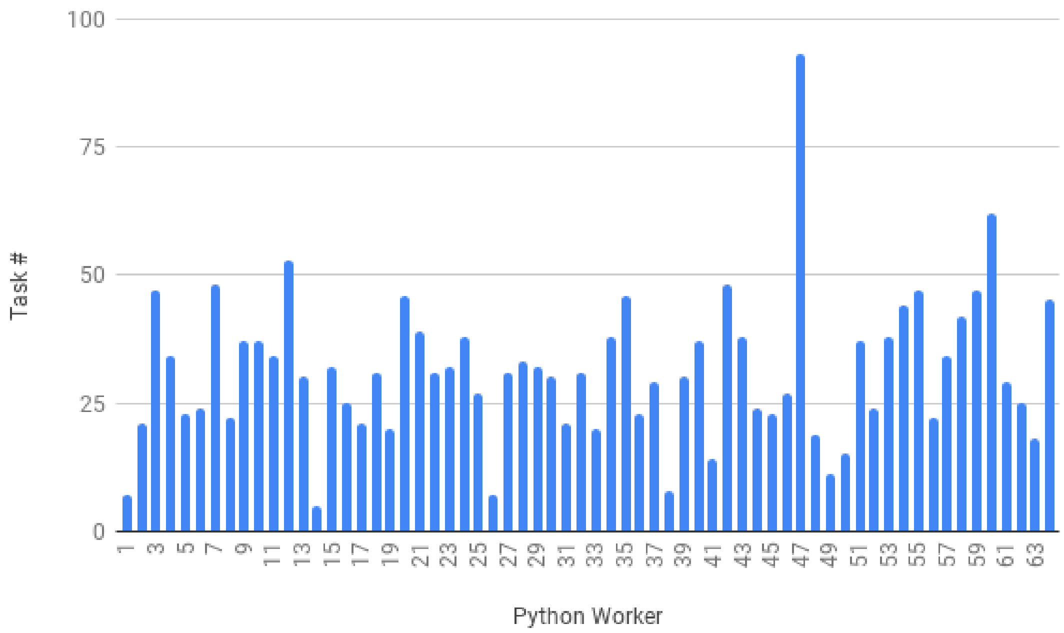

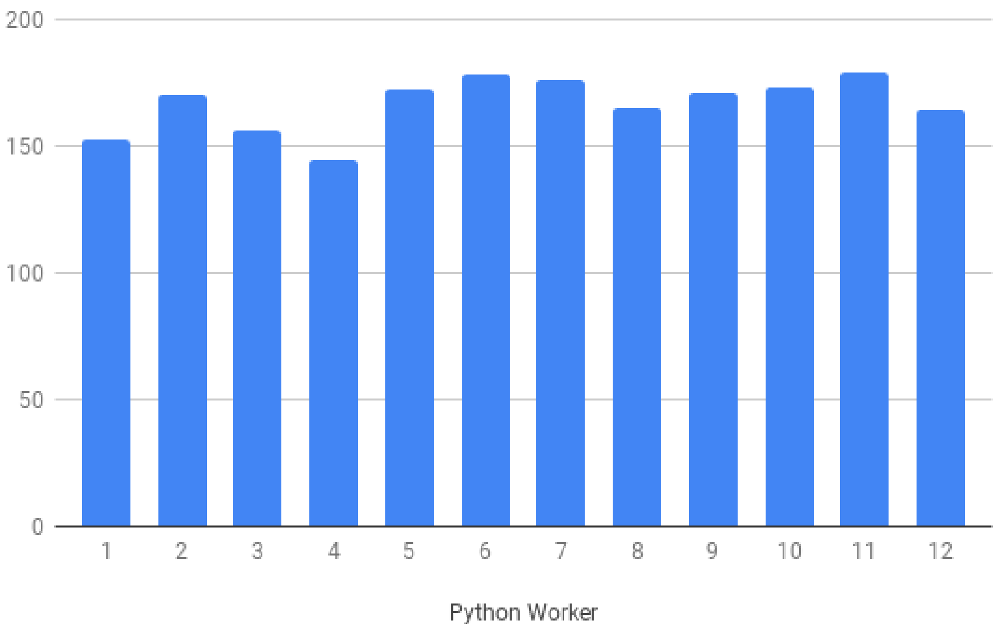

Deployment statistics

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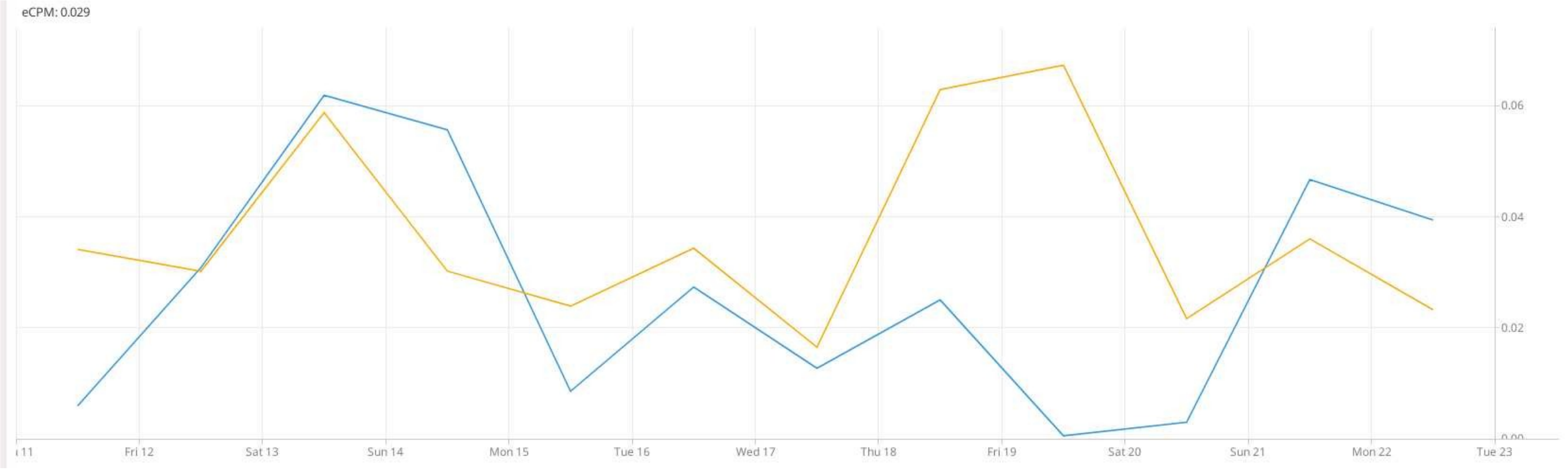


October 2018 results: revenue increase by 31%

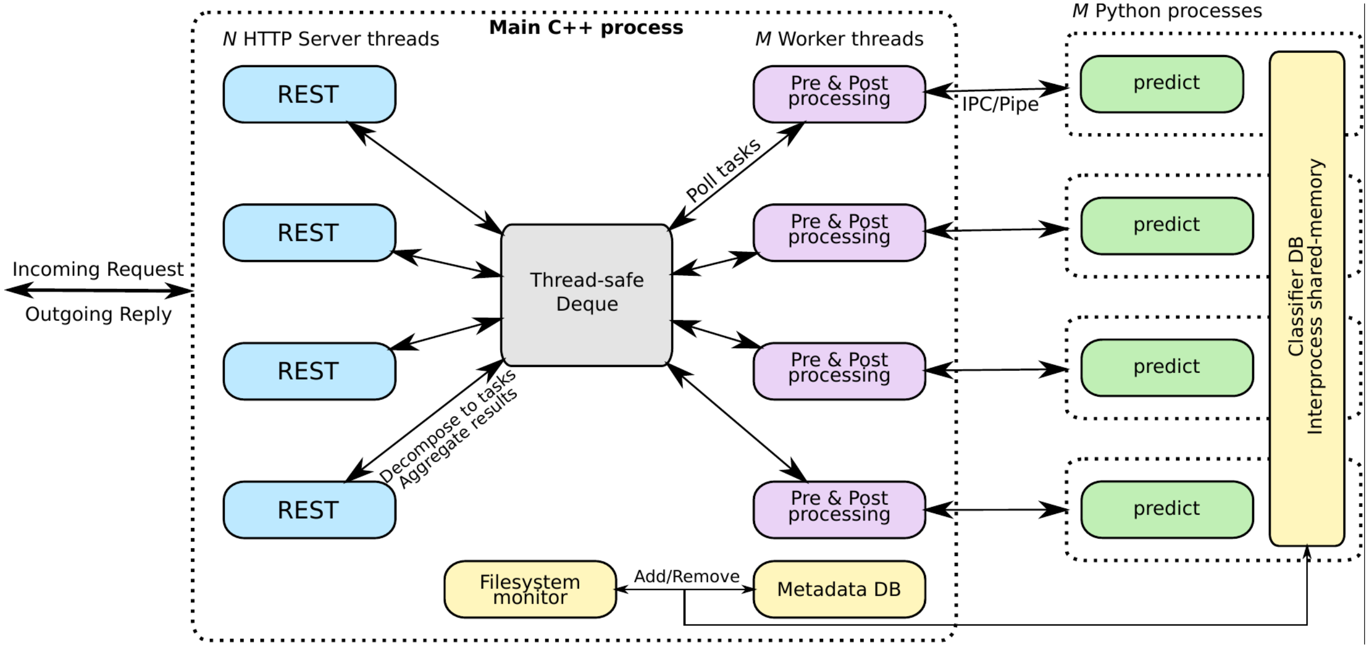
Conclusions

- Python is dead slow!
- Concurrency does not guarantee performance

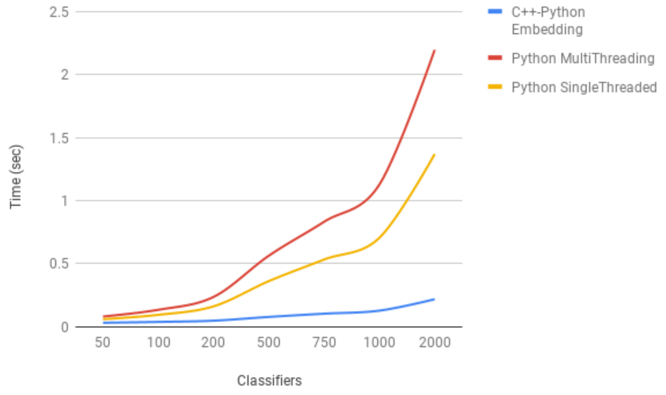
- Embedding Python into C++ enabled major performance improvements
- Development time was short
  - No need to evaluate a new ML platform

- Future work
  - improve work distribution, remove central queue
  - improve interprocess shared memory performance

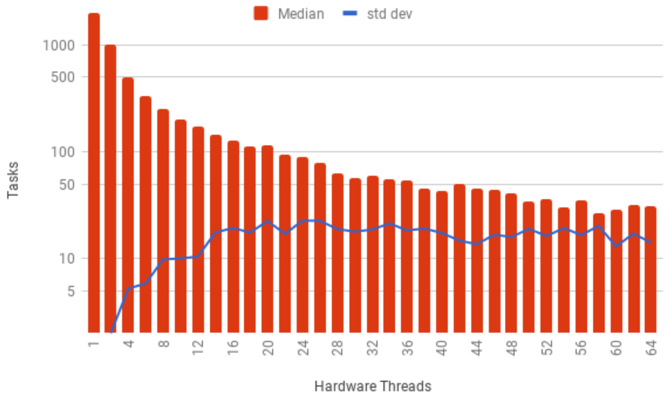
Thank you



Main C++ process
N HTTP Server threads
M Worker threads
REST
REST
REST
REST
Thread-safe Deque
Pre & Post processing
Pre & Post processing
Pre & Post processing
Pre & Post processing
Poll tasks
Decompose to tasks
Aggregate results
Incoming Request
Outgoing Reply
IPC/Pipe
M Python processes
predict
predict
predict
predict
Classifier DB Interprocess shared-memory
Filesystem monitor
Add/Remove
Metadata DB



C++-Python Embedding
Python MultiThreading
Python SingleThreaded
Time (sec)
2.5
2
1.5
1
0.5
0
50
100
200
500
750
1000
2000
Classifiers



Median
std dev
Tasks
1000
500
100
50
10
5
1
4
8
12
16
20
24
28
32
36
40
44
48
52
56
60
64
Hardware Threads