Henosis

A generalizable, cloud-native Python recommender framework

Valentino Constantinou, Ian Colwell – May 4th, 2018
1. Introduction

2. Recommendations Made Easier

3. Implementation & Proof of Concept

4. Wrap-Up

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1. Introduction
Leaders in the robotic exploration of the solar system.
We look to answer questions like…
What can Jupiter’s formation and evolution tell us about our solar system?
Was, or is, the Red Planet habitable to microbial life?
To answer these questions, we require robots like…
To design, build, and operate these spacecraft requires an enormous human undertaking.
And with that, the complete tracking of systems, failures, and anomalous behavior of spacecraft.
This requires some data... quite a bit of it!
A Data Scientist’s Snapshot of the Laboratory

- The Jet Propulsion Laboratory has existed since 1936.

- Now many data systems such as the Deep Space Network (DSN).

- Scope and volume of scientific data is large (NISAR will produce 3-5 TB daily).

A single DSN 70-meter radio antenna in Goldstone, CA
A Data Scientist’s Snapshot of the Laboratory

• Internal data historically less prevalent; data exists within organizations and groups.

• Considerable effort is being made to improve internal data collection and build data-driven services that can improve our internal processes and decision making.

a present-day view of JPL
User Evaluation & Technology Infusion Office

• A collection of data scientists, cloud engineers, software developers, and data visualization gurus.

• Our broad role as a team is to infuse new technologies into the way we do things at JPL.
We do some cool things!
Piloting the use of LSTM networks to detect anomalous behavior aboard spacecraft.
LSTM Anomaly Detection
Aboard the SMAP spacecraft in Earth orbit

various types of anomalies (point, contextual, collective)

an anomalous event for a single spacecraft telemetry stream (channel)
LSTM Anomaly Detection

User-interface allows operator to explore

LSTM anomaly detection D3 user interface
Developing **data visualization and exploration interfaces** that allow for user labeling of data.
Interactive Visualization

a generalized real-time stream of information

user-driven relationship exploration
2. Recommendations Made Easier
What is a recommender system?

• Recommender systems seek to predict some value a user would give to a particular item.
  • e.g. ratings, items to purchase, etc.
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- Two broad approaches:
  - **Collaborative Filtering**: provide users recommendations based on their similarity to others.
  - **Content-Based Filtering**: provide users recommendations based on their previous values for an item.
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• Recommender systems are everywhere… Here’s a few well-known examples.
Recommender Systems in Practice

• Amazon Online Store
  • Frequently Bought Together: recommends associated products through market basket analysis or similar means.
  • Recommendations for You in [category]: recommends individual products to you based on your past purchases and the purchases of others similar to you.
Recommender Systems in Practice

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• YouTube
  • **Recommended Videos**: recommends video content based off your recent history.

*These are opinions based on my individual experiences with the products and should not be interpreted as fact.
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• YouTube
  • **Recommended Videos**: recommends video content based off your recent history.

• Netflix
  • **Recommended Videos in [category]**: recommends video content within categories, such as *trending*.

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The Problem Failure Reporting System (PRS)
A time capsule of challenges and solutions

- Internal tool that allows engineers to submit Problem Failure Reports (PFRs) and Incident Surprise, Anomaly reports (ISAs).
  - 1. Document pre-launch test failures and post-launch operational anomalies experienced by spacecraft.
  - 2. Serve as both a record of past problems and of past solutions to the problems described.
The Problem Failure Reporting System (PRS)
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  • 1. Document pre-launch test failures and post-launch operational anomalies experienced by spacecraft.
  • 2. Serve as both a record of past problems and of past solutions to the problems described.

• Reports offer **complete record of JPL spacecraft anomalies**, characteristics, and solutions spanning more than 40 years.
The Problem Failure Reporting System (PRS)

Problem Failure Reports (PFRs) over the years

The Problem Failure Reporting System (PRS)

Important data but very time-consuming to populate

- Submitting reports is a time-consuming process.
- PRS forms contain over 40 fields, most of which are categorical. Some fields contain up to more than 50 classes.
- Data is very imbalanced.
The Problem Failure Reporting System (PRS)

Important data but very time-consuming to populate

• Submitting reports is a time-consuming process.
• PRS forms contain over 40 fields, most of which are categorical. Some fields contain up to more than 50 classes.
• Data is very imbalanced.
• Goal is to both improve the user experience and reduce the time needed to fill out PRS reports.
• Our solution is to provide form field recommendations to users dynamically as they populate the form.
What Does the Solution “Look Like”

A simple example

<table>
<thead>
<tr>
<th>Title</th>
</tr>
</thead>
<tbody>
<tr>
<td>e.g. CSSR Proof Test Failure</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>e.g. During post proof test disassembly of the CSSR, the set screws...</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Project Name</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th>Specific Environment</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th>Problem Failure Noted During</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th>Problem Type</th>
</tr>
</thead>
</table>
What Does the Solution “Look Like”

Overview

• *Henosis* is a cloud-based, open-sourced Python package that provides recommendations in a flexible and extensible framework.
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- Two broad development goals:
  - Generalizability
  - Ease of Use (user-driven design)
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  - Generalizability
  - Ease of Use (user-driven design)

- Open sourcing and generalizability were important goals from early on in the project.
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What is scikit-learn?

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What is scikit-learn?

- A collection of simple efficient tools for data mining, modeling, and analysis.
- Accessible to everyone that uses Python for data science.
- Open source, community-maintained, easy to use, and popular.
  - Lots of available coding examples.
  - Core members actively maintain and update code-base.
  - Integrates easily into many existing Python workflows.
Generalizable & Flexible

- Framework can be used with any *categorical* scikit-learn predictive model.
Generalizable & Flexible

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- Agnostic to data source $\rightarrow$ data sources reside outside the system.
  - “function tagging” allows us to bring in outside data or prep data $\rightarrow$ explain in later slides
Generalizable & Flexible

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  - “function tagging” allows us to bring in outside data or prep data → explain in later slides

- Use of Elasticsearch and Amazon S3 allows for deployment at scale, use of cloud services.
  - *Both are required to use Henosis → other options for future.*
Easy to Use

- User-Driven Development (UDD) was our approach from the start.

```python
from Henosis.model import Data, Models
from Henosis.server import Server
```

clean and easy imports
Easy to Use

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• Goal was to allow easy use by both data scientists and developers querying the framework for recommendations.

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clean and easy imports
Easy to Use

• User-Driven Development (UDD) was our approach from the start.

• Goal was to allow easy use by both data scientists and developers querying the framework for recommendations.
  • Developers simply query endpoint for recommendations. Different applications → unique but similar endpoints
    • System knows what to recommend through “missing tag”
  • Data scientists only call Henosis for splitting data or working with models
    • Models defined exactly as in scikit-learn

https://<host>/api/v0.1/recommend
example endpoint

{title: “ODSC”, difficulty: 999}
example request data
What Does the Solution “Look Like”
Framework architecture
What Does the Solution “Look Like”

Two user types we focused on

- Data Scientist
- Henosis Data
- Henosis Models

Outside Application (Developer) REST API

- Henosis Server
- elastic
- S3
What Does the Solution “Look Like”

Two user types we focused on

Data Scientist

Henosis Data

Henosis Models

Outside Application (Developer)

REST API

Henosis Server

elastic

S3
Useful Features

1. Top-N Recommendations
Useful Features

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2. Confidence Thresholding
Useful Features

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2. Confidence Thresholding
3. Averaging Model Predictions
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4. Bagging (bootstrap aggregation)
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1. Top-N Recommendations
2. Confidence Thresholding
3. Averaging Model Predictions
4. Bagging (bootstrap aggregation)
5. Built-in Server and API
Useful Features: Top-N Recommendations

- Providing only the most likely class for a given categorical field limits usability in some use cases.

- Bucketing the top $n$ predictions decreases the likelihood of providing incorrect recommendations $\Rightarrow$ increases likelihood of appropriate response.

- Bucketing also allows for a little bit more “slack” for tough modeling problems.

\[
\begin{align*}
\text{Top-N} &= 1 \quad 2 \quad 3 \\
\text{Likelihood} &= 0.35 \quad + \quad 0.45 \quad + \quad 0.48
\end{align*}
\]

Specific Environment

Recommended: Ambient - Clean Room; Ambient - In Doors; Low Temp, Vacuum;
Useful Features: Top-N Recommendations

Examining accuracy

Examining precision, recall, F-Score
Useful Features: Confidence Thresholding

- Idea is to provide recommendations only when confident of the result.

- Examine max bucketed class probability between true and false recommendations.

\[
[\text{In Doors}, \text{Cryogenic Testing}, \text{Orbit}]
\]
\[
[0.35, 0.1, 0.03]
\]

- predicted labels
- predicted probabilities

single prediction determined cut-off value

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Useful Features: Confidence Thresholding

- How do precision, recall, F-score improve as the percentage of withheld recommendations increases?

- Easy to specify → threshold is an optional parameter when deploying model.
Useful Features: Averaging Model Predictions

• Intuition: using multiple types of models better captures data distribution and relationships → improves performance

• Henosis averages predicted probabilities for each class across models → provides ranked result

• Using more than one model per field allows for multiple model types, data sources.
Useful Features: Bagging Model Predictions
(also known as bootstrap aggregation)

• Intuition: sampling data with replacement → reduces overfitting

• By randomly sampling before each model is fit, can easily achieve bagging.

• Bagging can improve performance when classes in the dependent variable are sparsely represented.

Useful Features: Function Tagging

• What if I want to clean the text from a form field?

• What if I want to grab new data from somewhere besides the form for my models?
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Useful Features: Function Tagging

1. Grab field “title” from API request.

Grab Data from an API

1. Grab field “ID” from API request.

Text Cleaning

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Useful Features: Function Tagging

Text Cleaning
1. Grab field “title” from API request.
2. Clean the text by removing stopwords, lemmatizing, etc.

Grab Data from an API
1. Grab field “ID” from API request.
2. Using ID, query HR database for demographic information.
Useful Features: Function Tagging

Text Cleaning

1. Grab field “title” from API request.
2. Clean the text by removing stopwords, lemmatizing, etc.
3. Insert this cleaned text as a new field called “cleanText”.

Grab Data from an API

1. Grab field “ID” from API request.
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3. Insert collected demographic information as new fields (age, team, etc.).
Useful Features: Function Tagging

**Text Cleaning**

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4. Deployed model uses “cleanText” to provide recommendations.

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5. Returned model-specific recommendation has used data from outside the original API request.
Useful Features: Built-In Server and API

• Henosis comes built in with a simple gevent WSGI + Flask server for providing recommendations.

• API has endpoints:
  • /recommend (provides recommendations)
  • /models (provides model information)
  • /requestlog (provides logs from each request made to the system)

• Running the server simply consists of an import, specification of a configuration file, and calling function within the Server class.
Useful Features: Built-In Server and API
/recommend

• This API endpoint is the “bread & butter” of the API.
• Query is a flat JSON file containing (key, value) pairs where:
  • **Key:** indicates variable name, should be the same as training set
  • **Value:** a raw value to use in making predictions
    • unique “missing tag” is used by system to determine which fields need recommendations

```json
query
{
  'variableOne': '999999',
  'variableTwo': 'Spaceman',
  'variableThree': '999999',
}

response
{
  "variableOne": "Proton Beam",
  "variableTwo": "Spaceman",
  "variableThree": "Liquid Nitrogen Resistant Gloves"
}
```
Useful Features: Built-In Server and API

/models

- This endpoint returns information about models stored and deployed in the system.
- Can retrieve all models or only models that meet specific condition.
  - e.g. `deployed = true`

```json
response

"callCount": 30,
"dependent": "variableTwo",
"deployed": true,
"encoderPath": "encoder_variableTwo_1.pickle",
"encoderType": "CountVectorizer",
"testF1": 0.9008452056839288,
"testPrecision": 0.9044056750340173,
"testRecall": 0.9019607843137255,

"independent": [
  {
    "generator_path": "clean_text.pickle",
    "inputs": [
      "title"
    ],
    "name": "cleanText"
  }
],
```
Useful Features: Built-In Server and API

:requestlog

- This endpoint returns information about models stored and deployed in the system.
- Can retrieve all request logs or only request logs that meet specific condition.
  - e.g. `responseStatusCode = 200`

```json
"sessionId": "a1c5b9a7f01d4f30a6cb13b2390fc2ac",
"sessionExpireDate": "2018-02-07T10:51:12",
"timeIn": "2018-02-21T05:42:50",
"timeOut": "2018-02-21T05:42:52",
"timeElapsed": 2.294113159176875,
"responseStatusCode": 200,
"responseDescription": "200 OK",

"recommendations": {
  "projectName": ["projectOne"],
},

"missingFields": ["projectName"],

"modelsQueried": ["be4d26d624a6408abd105b015e0526b3"]
```
Summary of Overviewed Features

• Henosis is a general, cloud-based recommender framework. Goal → improve the usability and ease of use of deploying recommender systems for categorical fields.
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- Henosis is a general, cloud-based recommender framework. Goal → improve the usability and ease of use of deploying recommender systems for categorical fields.
- Can bucket recommendations to provide users with several recommendations.
- Can threshold recommendations based on confidence, and fetch or process data from outside sources using tagged functions.
- Comes with WSGI + Flask server for providing recommendations.
Summary of Overviewed Features

- Henosis is a general, cloud-based recommender framework. Goal → improve the usability and ease of use of deploying recommender systems for categorical fields.

- Can bucket recommendations to provide users with several recommendations.
- Can threshold recommendations based on confidence, and fetch or process data from outside sources using tagged functions.
- Comes with WSGI + Flask server for providing recommendations.

- Other useful features in system, such as (but not limited to):
  - preloading models into memory and periodically refreshing those models
  - the ability to provide a single recommendation through majority vote (no probabilities)
  - simple API authorization
  - ability to track sessions in the using the request log
Henosis in Practice

A simple modeling workflow example

```python
from Henosis.model import Data, Models

def read_data_from_csv(data):
    # read in data from a csv
    data = Data()
    data.load('file.csv')
    print(data.head())

# split data
def split_data(data):
    data.test_train_split(  
        data[X_vars],  
        data[y_var],  
        share_train=0.8  
    )

# fit a model (use any categorical scikit-learn model)
# this is where you do your "magic!"
model = Models().SKModel(MultinomialNB(alpha=0.25))
model.train(data)
model.test(data)

# print results
print(model.train_results)
print(model.test_results)

# store the model in S3 and Elasticsearch
store_model(model, server_config=s,  
    model_path='model_' + y_var + '_1.pickle',  
    encoder_path='encoder_' + y_var + '_1.pickle',  
    encoder=count_vect
)

# deploy a model for use
model.deploy(  
    server_config=s,  
    deploy=True
)
```

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Henosis in Practice

A simple server deployment example

```python
from Henosis.server import Server

# run the server
s = Server().config(config_yml_path='config.yml')
s.run()
```
Henosis in Practice

Configuration

# ElasticSearch
elasticsearch:
  host: 'https://<host>:<port>'
  verify: False
  auth: {'<python/tuple': ['<username>', '<password>']}
  models:
    index: '/model'
    request_log:
      index: '/requestlog'

# AWS S3
aws_s3:
  region: '<region>'
  bucket: '<bucket>'
  key: '<<aws_key>'
  secret: '<<aws_secret>'

# Api
api:
  host: 'http://localhost:5005'
  index: '/api'
  version: '/v0.1'
  missing: '999999'
  sessionExpiration: 10
  auth: {'<python/tuple': ['<username>', '<password>']}

# Models
models:
  preload_pickles: True
  refresh_pickles: 1440 # in minutes
  predict_probabilities: True
  top_n: 3
3. Implementation & Proof of Concept
PRS 2.0 deployment architecture builds on top of the open-source framework.
The PRS 2.0 Architecture

The complete picture

- **PRS 2.0** (outside application)
- **data sources**
- **system dashboard**
- **model / request information**
- **Docker containers**
- **S3** (holds models)
- **Kubernetes Container Orchestration on EC2**
- **AWS GovCloud**
- **Jupyter** (data prep / modeling (offline))

Data sources include:
- AWS GovCloud
- Kubernetes Container Orchestration on EC2
- Docker containers
- S3

System components include:
- Kibana
- Elastic
- PRS
- IBAT

The complete picture illustrates the architecture and components of PRS 2.0.
The PRS 2.0 Architecture

Steps to deployment: grab data
The PRS 2.0 Architecture

Steps to deployment: work your magic!

PRS 2.0 (outside application)

- Data sources
  - AWS GovCloud
  - Kubernetes Container Orchestration on EC2
  - Docker containers
  - S3

- System dashboard
  - Kibana

- Model / request information
  - Elastic

- Steps to deployment: work your magic!
The PRS 2.0 Architecture

Steps to deployment: push to cloud
The PRS 2.0 Architecture

Steps to deployment: store models
The PRS 2.0 Architecture

Steps to deployment: containerize
The PRS 2.0 Architecture

Steps to deployment: use Docker
The PRS 2.0 Architecture

Steps to deployment: models added to index
The PRS 2.0 Architecture

Retrieving recommendations: make request

- **AWS GovCloud**
  - Kubernetes Container Orchestration on EC2
    - Docker containers
      - **S3**
        - holds models
      - **PRS**
      - **IBAT**
        - data sources
    - **elastic**
      - model / request information
    - **kibana**
      - system dashboard
  - **learn**
    - data prep / modeling (offline)
    - **jupyter**

PRS 2.0 (outside application)
The PRS 2.0 Architecture

Steps to deployment: Henosis processes
The PRS 2.0 Architecture

Steps to deployment: logs added to index

- AWS GovCloud
- Kubernetes Container Orchestration on EC2
- Docker containers
- S3 holds models
- Jupyter data prep / modeling (offline)
- PRS 2.0 (outside application)
- PRS
- IBAT data sources
- kibana system dashboard
- elastic model / request information
- EC2 + kubernetes
- May 4, 2018

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The PRS 2.0 Architecture

Retrieving recommendations: receive
The PRS 2.0 Architecture

Viewing system performance: Kibana
PRS 2.0 Stress (Load) Testing
Testing scalability and reliability

- Used Python library called *Locust* to perform stress testing of PRS 2.0 recommender system.
PRS 2.0 Stress (Load) Testing

Testing scalability and reliability

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- Six deployed models, one for each field.

- 4 Docker containers:
  - 8GB ram each
  - M4.4xlarge AWS EC2 instances

- Generated dummy data and bombarded system with requests.
PRS 2.0 Stress (Load) Testing
Testing scalability and reliability

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- Six deployed models, one for each field.
- 4 Docker containers:
  - 8GB ram each
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- Generated dummy data and bombarded system with requests.

- Successfully handled 800 simultaneous users averaging ~ 12 requests (recommendations) per second, 1% error rate.
Kibana

Kibana allows for the exploration & visualization of data in Elasticsearch

We’re using Kibana in our deployment to show:

- Information about models (above) and associated fields
- Request logs, such as session actions, latency, models queried, etc.
4. Wrap-Up
We’ve learned a lot of lessons along the way.
**L1.** Start with the simplest end-to-end pipeline, and build up from there.
L2. Fit into and compliment your users’ workflow.
L3. Be general as possible, allow for extensibility.
L5. Keep latency in mind → use fast models and functions!
L6. Illustrate through real-time example and demonstration to solidify concepts.
Future Work

• It’s an open source project. We welcome pull requests, open issues, or ideas for future work!
  • (there are several open issues on Github if you’re feeling inclined)
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• Add the ability to support regression models.
• Explore the use of collaborative filtering and association rules (market basket analysis) in the framework.
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• Add the ability to support regression models.
• Explore the use of collaborative filtering and association rules (market basket analysis) in the framework.
• Better track individual recommendation requests to quantify which recommendations are used, when, and from which model(s).
Future Work

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• Add the ability to support regression models.
• Explore the use of collaborative filtering and association rules (market basket analysis) in the framework.
• Better track individual recommendation requests to quantify which recommendations are used, when, and from which model(s).
• A/B testing with PRS 2.0 to measure time savings, dollar impact.
• Many others!
Some Acknowledgements

- **Ian Colwell**: for the very consistent and informative feedback on framework development. Such an awesome project partner!

- This work would not be possible without the generous support from the Office of Safety and Mission Success (5X).
  - **Leslie Callum**: for organizing information and people between 5X and our office (no small feat!)
  - **Harold Schone**: for believing in and pushing for using data science in internal applications on the lab.

- **Kyle Hundman**: for technical expertise and feedback.
- **Paul Ramirez**: for spurring ideas and further thinking.
- **Kevin Reelfs and Tom Soderstrom**: for continued support, interest, and advocating of our team’s projects.
Give it a try!

*Framework:* [https://www.github.com/vc1492a/henosis](https://www.github.com/vc1492a/henosis)

*Documentation:* [https://www.henosis.io](https://www.henosis.io)

Let’s chat!

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Appendix
Why is it called Henosis?

Give me a word, any word, and I show you how the root of that word is Greek.