

R Workflows in Azure Machine Learning for Athletic Data Analysis

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Data for High Performance Athletics

Trying to keep athletes

- Healthy
- Available
- Performing well

Measured by

- Load & volume
- Performance metrics & tests
- Injuries

Online platforms host & automate reports

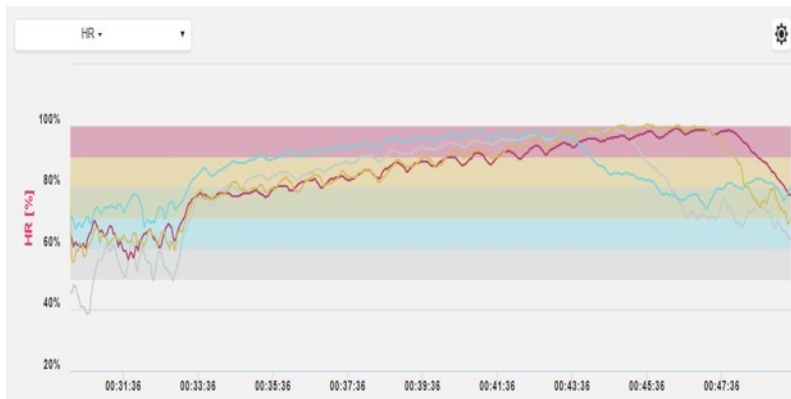
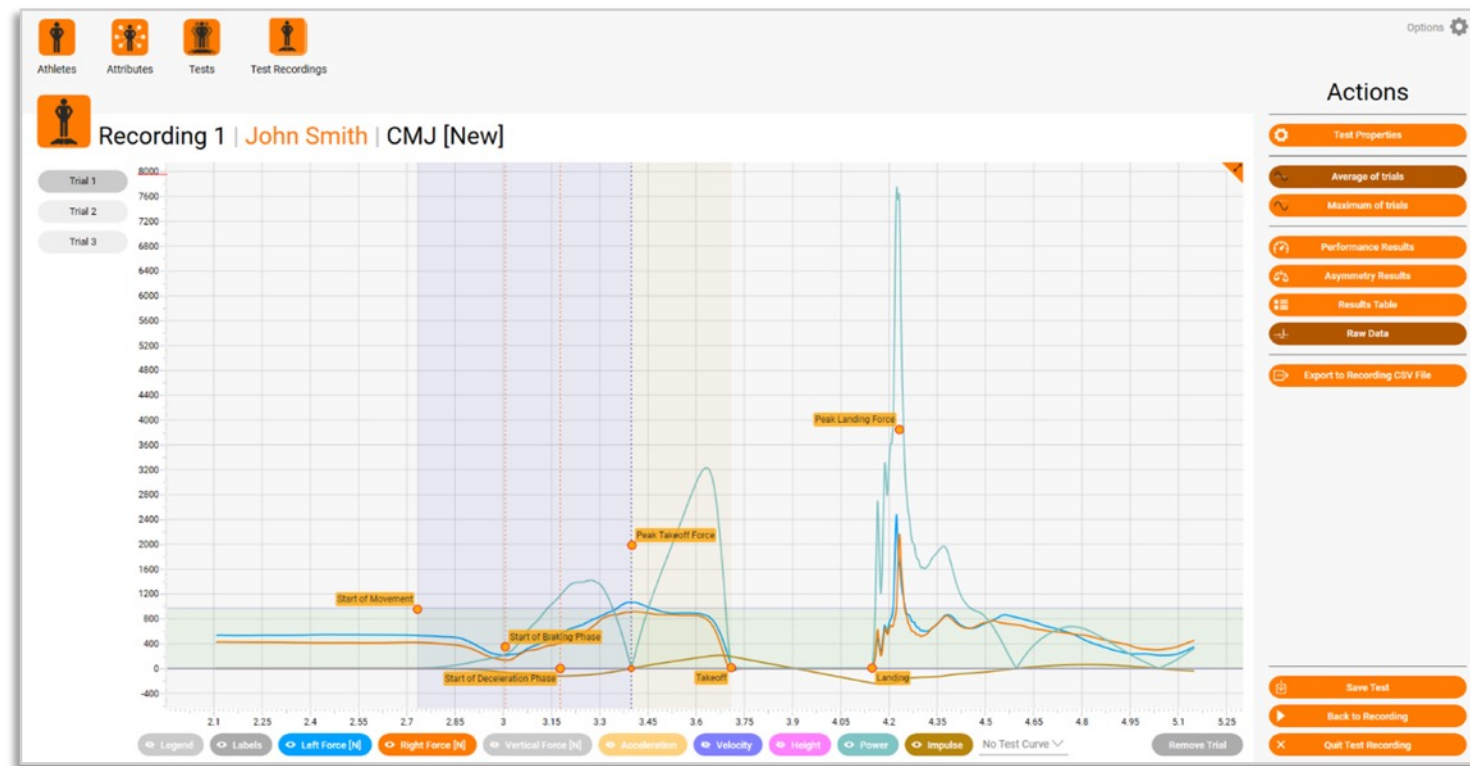
Data available to export manually to Excel or through API to R

Data used by Sports science, S&C, sport coaches, trainers and more

Working Fast

Day-to-Day Athletics Operations

- Data collection
 - Live, daily, weekly, longer
- Storage
- Basic analysis & reporting
- Decision making



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Working Slow

Data Science, Research, Long-Term Goals

- Data cleaning
- In-depth reports & aggregation
- Advanced analysis
- Connecting the Dots

Conflicting Needs

Changing data, constant additions, too many versions

Can't have controlled experiment

Too many bottlenecks and stopping points

Old Framework

FAST

- Automated reports via dashboard

Difficult for Slow Work

- What do we put on the dashboard? New metrics?
- No central source for raw instrument data
- Variety of IDs from different instrument interfaces
- Data in different versions, different places, different files
- CSV creation and pull was slow, too many CSVs....

New Framework Goals

- Improve outcomes (more complete, valid, actionable data)
 - Lower barriers to more complex data science & analytics
- Aggregate data in one place
 - Easier data cleaning, validation, analysis
 - Unify player ID
- More compute power
 - Ability to collaborate & compute easier
- Less bottlenecks- duplication, updates, incomplete data
- Ability to share findings more easily

What is Azure?

Analysis in
Jupyter
Notebook (R,
Python, Julia)



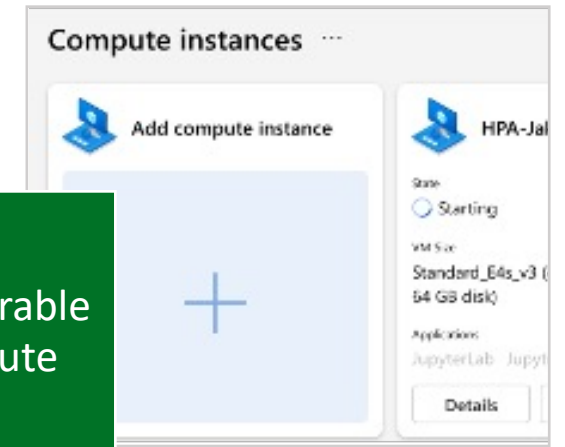
Terminal

Welcome to the Azure Machine Learning terminal.

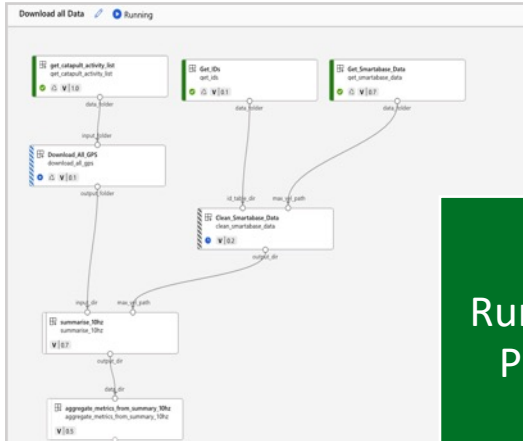
Enter "git clone [url]" to clone a repository into the Azure Machine Learning terminal, navigate to the repository directory, and run "az ml --help" to learn about the available commands.

Use "az login --identity" to login to the Azure Machine Learning environment.

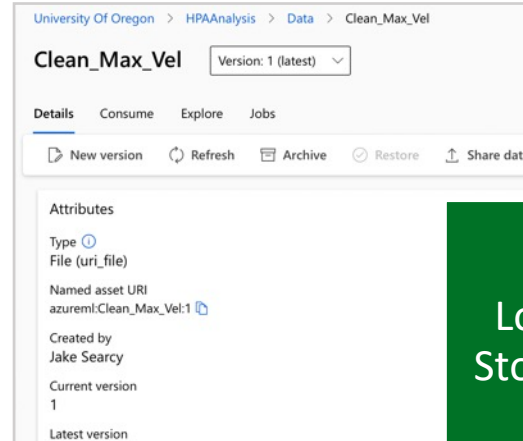
Configurable
Compute



Running Job
Pipelines



Loading &
Storing Data



Microsoft

Pick an account

enk@uoregon.edu

Use another account

Secured with
UO login

New Framework

FAST

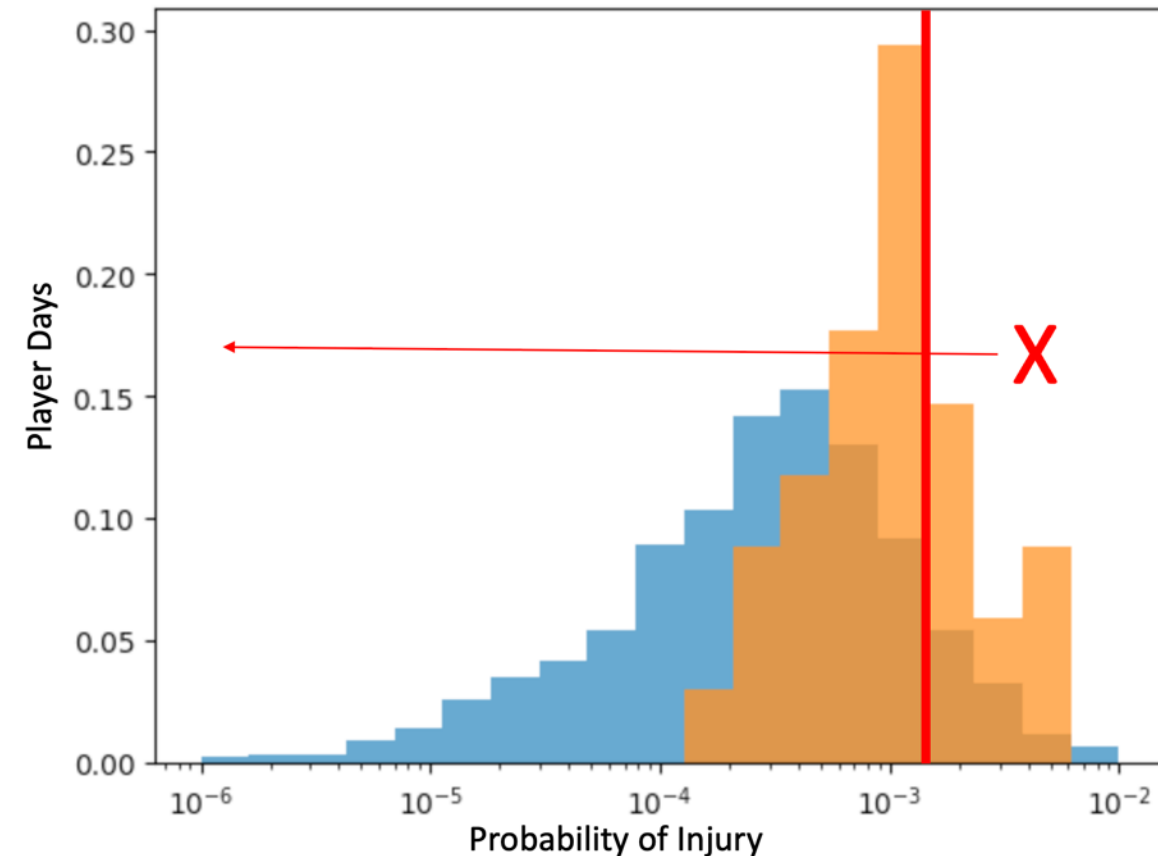
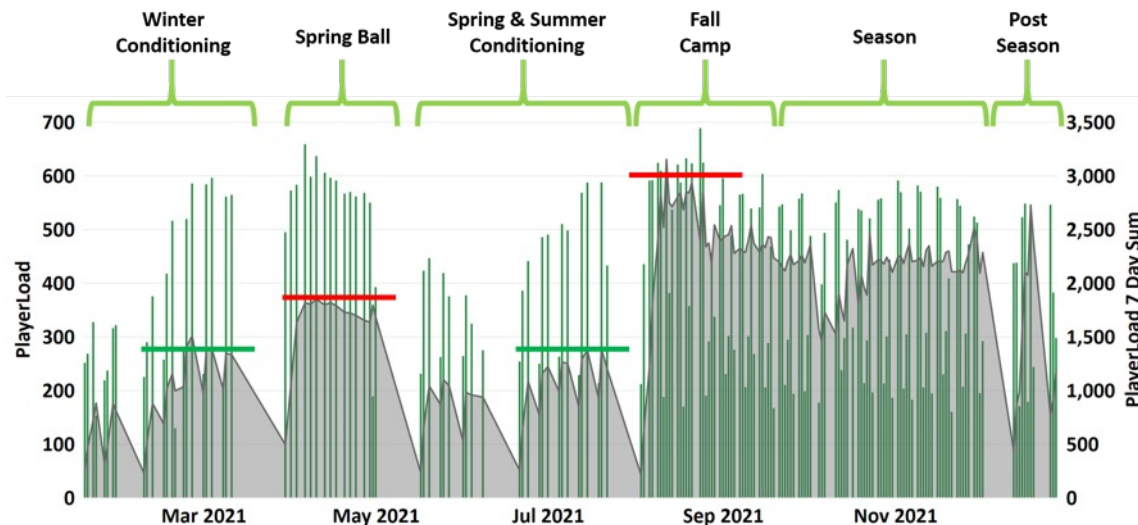
- Automated reports via dashboard → Still in use

Better for Slow Work

- What do we put on the dashboard? New metrics? → Able to step back from constant stream of data
- No central source for raw instrument data → Able to pull from all APIs
- Variety of IDs from different instrument interfaces → Easier merging
- Data in different versions, different places, different files → Data Lives in one place
- CSV creation and pull was slow, too many CSVs.... → Easier to maintain the most recent version, quicker due to higher computing power

What we are looking at now

- Hamstring injury predictability
- Discrete time survival models
- Differences between genders
 - Relationships between metrics
 - Response to training



Countermovement Jump Analysis

Kinetic Variables of Interest

Eccentric Rate of Force Development

An athlete's ability to generate force during the eccentric phase of the movement

Jump Height

The global output of the stretch shortening cycle



Stretch-Shortening Cycle
(SSC)

Countermovement Jump Analysis

Kinetic Variables of Interest

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The global output of the stretch shortening cycle

Research Questions

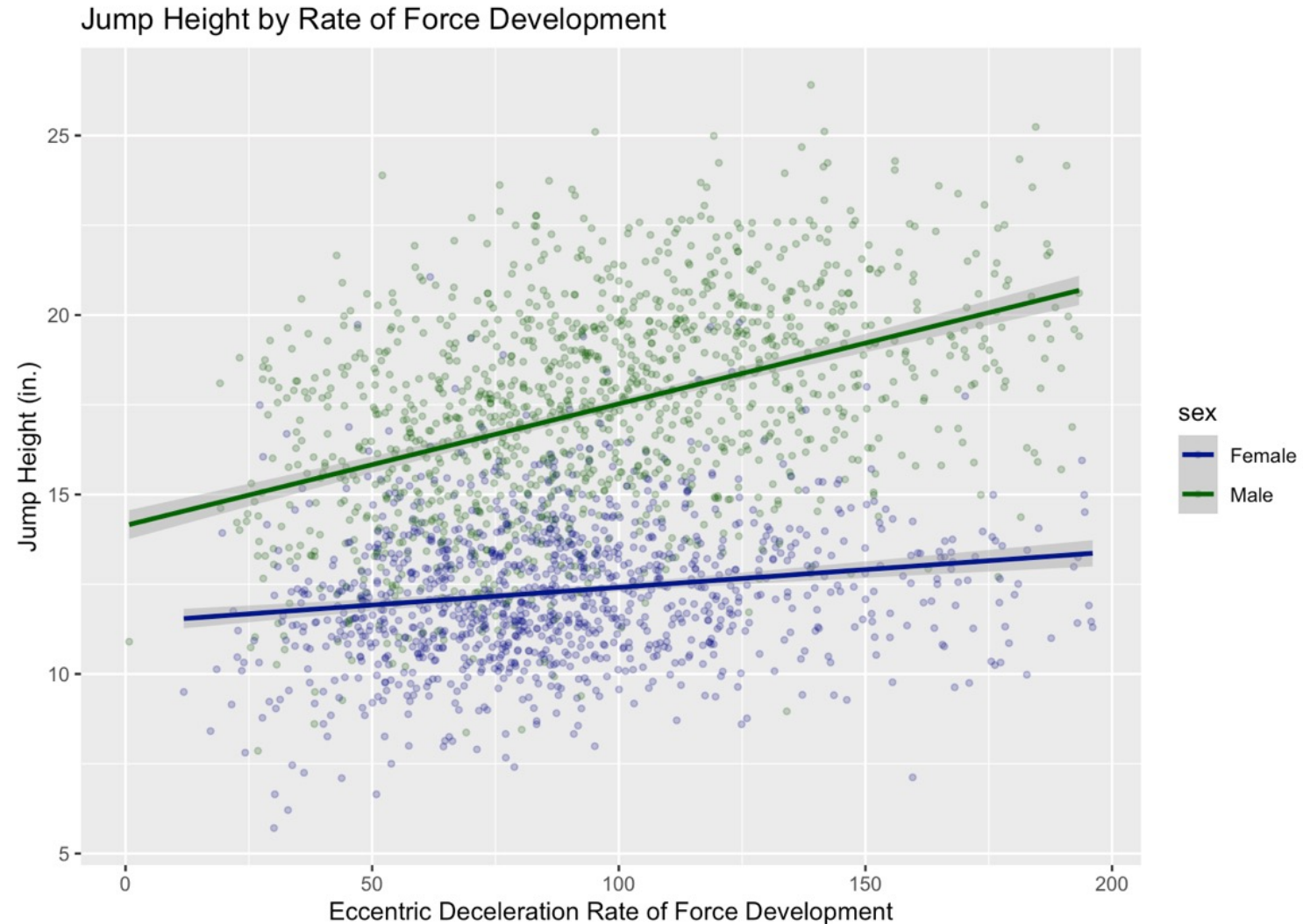
Is there a difference in relationship between the two variables of interest?

Can we change Jump Height or Eccentric Rate of Force Development over time as a result of training?

Gender Differences

Relationship between Eccentric Deceleration Rate of Force Development and Jump Height

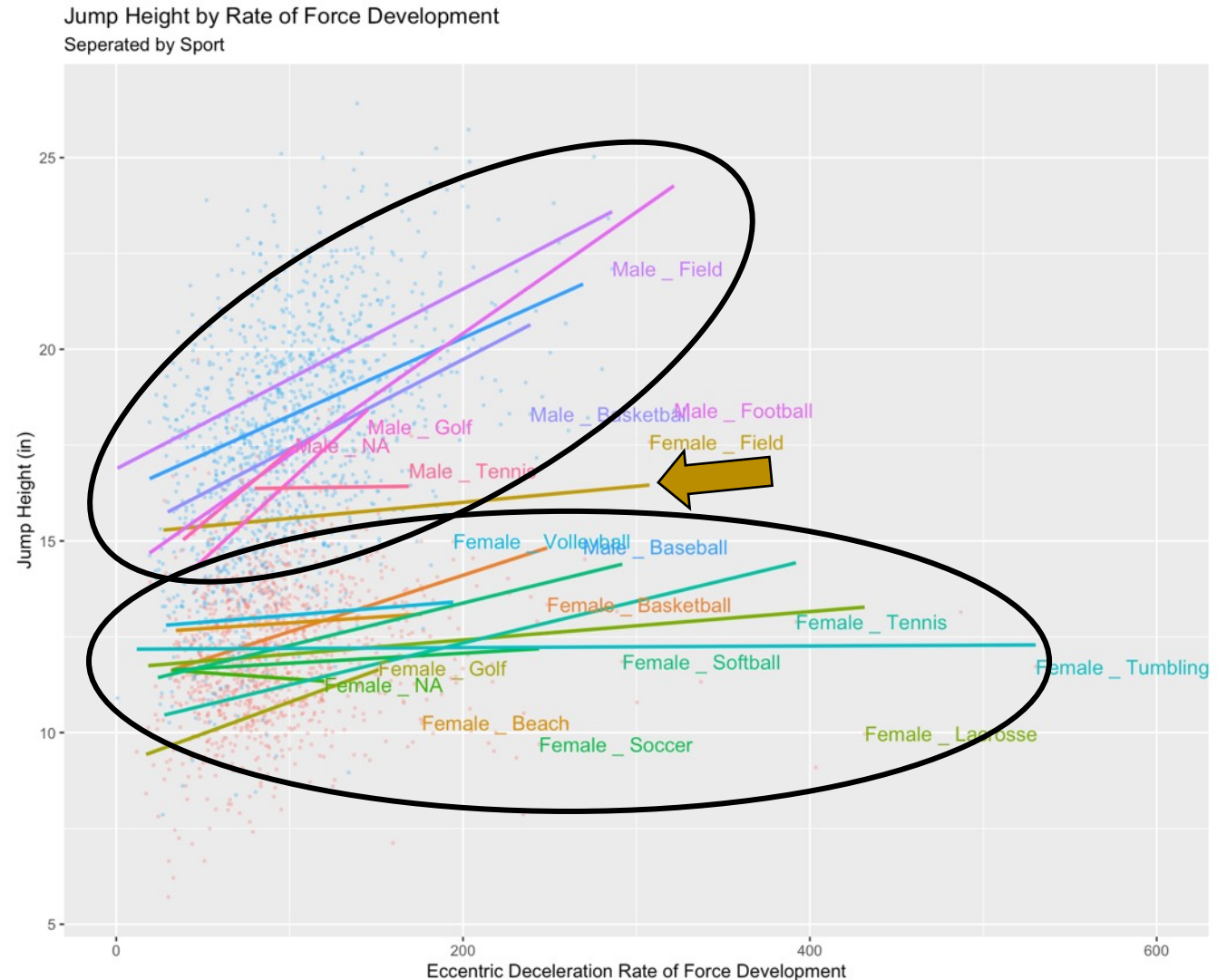
Higher Eccentric Deceleration Rate of Force Development (RFD) has stronger correlation with higher jump height for men than for women



Regression Model

Jump Height regressed by RFD, sport (separated by gender) and interaction term between gender & RFD

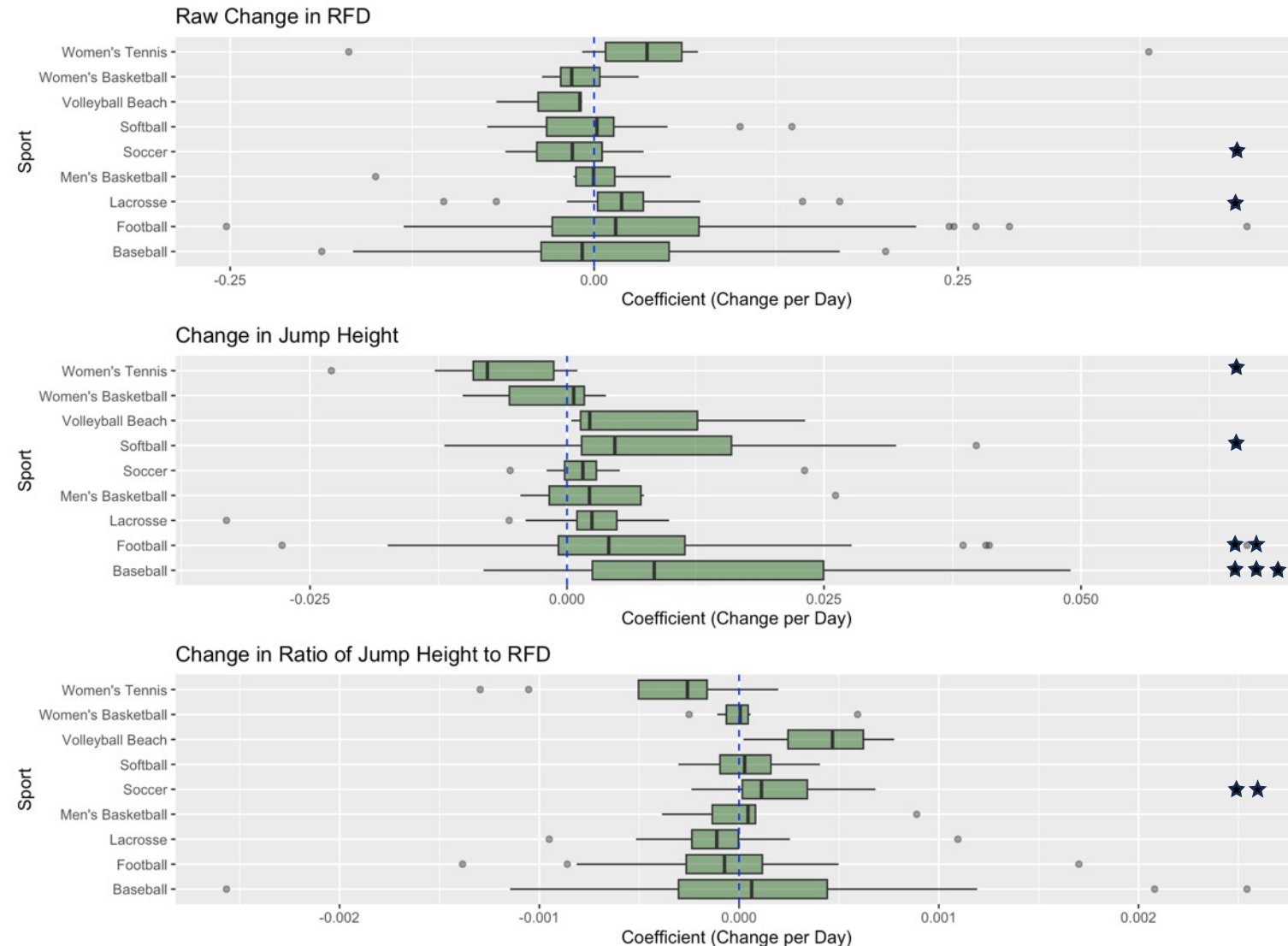
- Men's sports generally have a significantly higher coefficient than the baseline, with a few exceptions
- Interested in sports and individuals that break this pattern or improve over time
 - Can we train this?



Training Response

Individual change regressed over their entire time at Oregon

- Trained two years at Oregon, 10 tests
- RFD over time
 - Decrease for Soccer, increase for Lacrosse
- Jump Height over time
 - Decrease for Women's Tennis, increase for Softball, Football, Baseball
- Ratio of Jump Height/RFD over time
 - Increase for Soccer



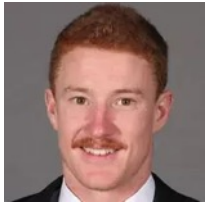
Acknowledgements



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Performance Alliance

Wu Tsai Human Performance Alliance