

# Pandas and Scikit-Learn

Andrew H. Fagg

Symbiotic Computing Laboratory

# Is Jupyter Working?

# Test Data Sets

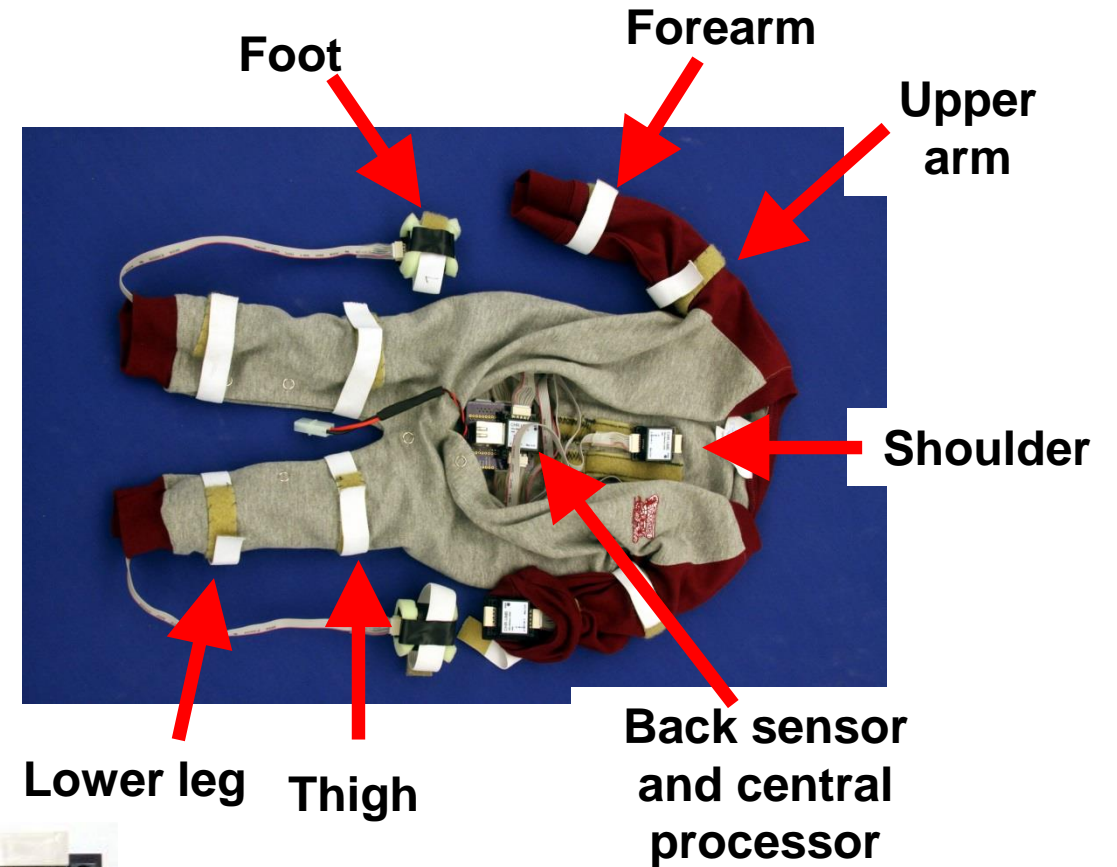
/home2/fagg/datasets

- book/housing/: Housing dataset from the book
- baby1/: Infant kinematic datasets
  - k1: basic table
  - k2: much larger table, including some robot information

# Kinematic Capture Suit

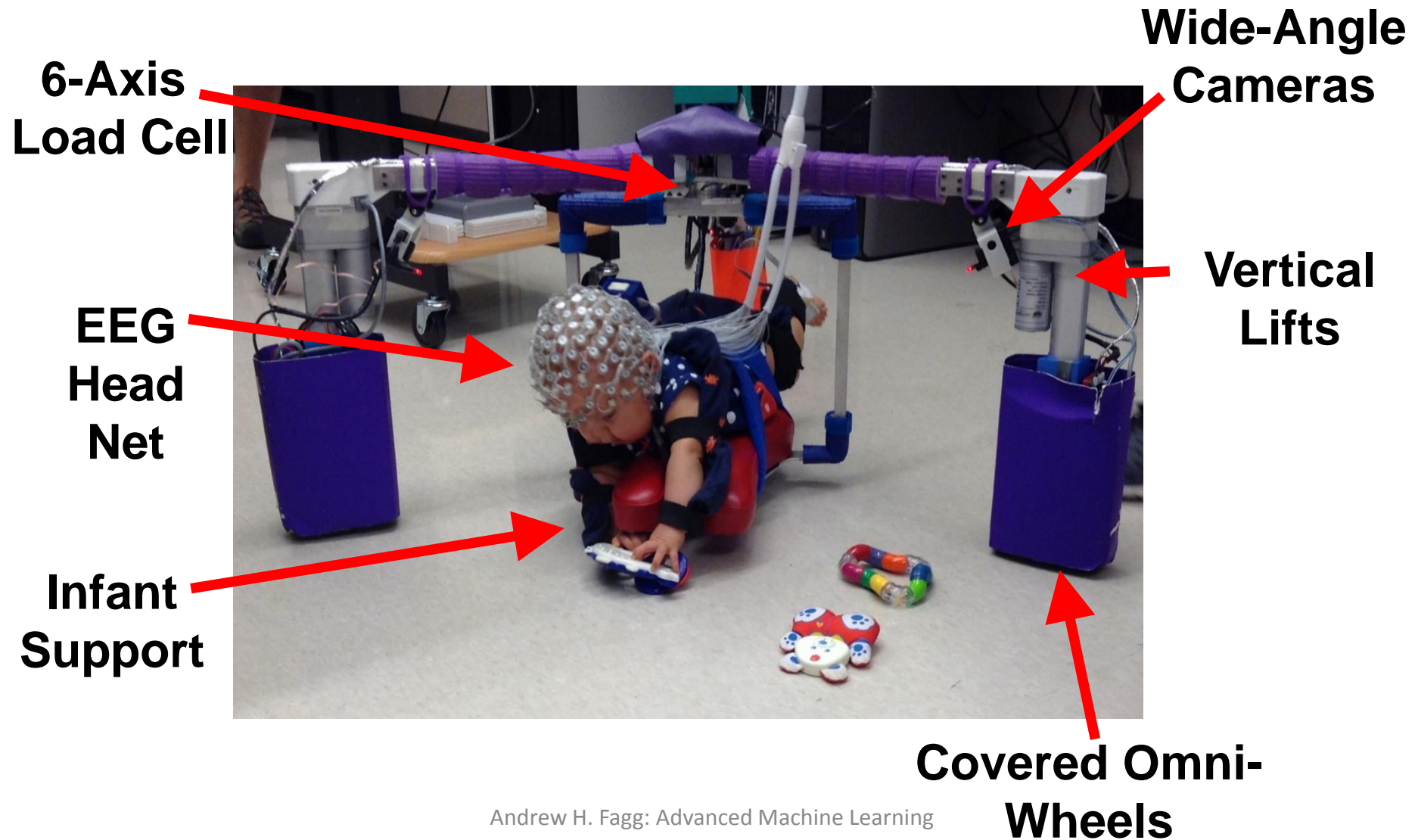
IMU-based kinematic suit

- 12 sensors mounted in suit
- Real-time reconstruction of body posture
- Recognition of crawling-like actions



Southerland (2012)

# SIPPC Crawling Assistant



# Infant-Robot Interaction

Three modes of interaction:

- **Force control:** robot velocity is linearly related to ground reaction forces
- **Power steering:** small ground reaction forces produce a substantial robot movement
- **Gesture-based control:** recognized crawling-like movements produce robot movement

# Python Lists

Python mechanism for implementing arrays

- Zero-indexed
- Bounds checking
- Elements can contain arbitrary data (including other arrays)

```
b = (2, 4, 7, 8, 1, 'foo', 'bar', 42)
```

# Python Lists

```
b = (2, 4, 7, 8, 1, 'foo', 'bar', 42)
```

```
b[3]
```

**8**

```
b[6]
```

**'bar'**

```
# Reslicing
```

```
b[2:4]
```

**(7, 8)**



# Fundamental Data Structure in Python: Dictionaries

Implementation of a map

- Map contains a set of keys (keys are unique)
- Each key has arbitrary data associated with it

```
c = {0: 'zero', 5: 'five', 'foo': 'bar', 'baz': (42, 37) }
```

# Dictionaries

```
c = {0: 'zero', 5: 'five', 'foo': 'bar', 'baz': (42, 37)}
```

```
c[0]
```

```
'zero'
```

```
c[1]
```

```
KeyError
```

```
c['foo']
```

```
'bar'
```

```
c['bar']
```

```
KeyError
```

```
c['baz']
```

```
(42, 37)
```

# Python Objects

Proper objects in the *object oriented programming* sense

- Instance variables: state describing the object
- Instance methods: methods that can be executed with respect to the object
- Underlying representation is a dictionary
  - Python is happy to allow us to make use of this fact...

# An Example ...

```
class testClass:
```

```
    def __init__(self):
```

```
        self.name = 'foo'
```

```
        self.value = 5
```

```
    def increment(self):
```

```
        self.value = self.value + 1
```

**Constructor**



**Initialize instance variables**



**Another instance method**



# Using our Class

```
# Create a new instance
```

```
a = testClass()
```

```
a.value
```

```
5
```

```
a.increment()
```

```
a.value
```

```
6
```

```
a.name
```

```
'foo'
```

# Using our Class

```
a.increment
```

```
<bound method testClass.increment of  
<__main__.testClass object at  
0x7f7480431c88>>
```

- When you want to call a method, make sure you include the parens!

# Modified Class

```
class testClass:
    def __init__(self):
        self.name = 'foo'
        self.value = 5
    def increment(self):
        self.value = self.value + 1

    def __getitem__(self, i):
        if i == 0:
            return self.name
        elif i == 1:
            return self.value
        else:
            return None
```



**Allows array-like  
access**

# Using the New Access Method

```
a = testClass()
```

```
a[1]
```

**5**

```
a.increment()
```

```
a[1]
```

**6**

```
a[0]
```

**'foo'**



# Pandas

Toolkit for data handling and analysis

- File I/O, including csv files
- Hooks for visualization
- Basic statistics
- Data selection and massaging
- SQL-type operations

# Data Structures

Two primary Python classes:

- **Series: 1D data**
  - Indexed by integer location in the array or by some index variable (which can have string values)
- **DataFrame: 2D data**
  - Each dimension indexed by integer index or other index variable

- Live demo...

- Live demo continued:
  - Plotting with Pandas & specifying horizontal axis variable

- Pipeline demo

# Model Construction (Learning)

We want the “best” model as possible. One approach:

- Use the available data to select model parameters that optimize some performance metric
- Deploy the model

# Model Construction (Learning)

How do we know that the model is really all that good?

# Model Construction (Learning)

How do we know that the model is really all that good?

- We don't: our model could very well have ***overfit*** the data



# Model Learning

Goal: we want our models to perform well on future data sets

- Our challenge is how to measure this \*now\*, so that we can make proper decisions about which model or model parameterization to choose
- Note the relationship with scientific theories: a good scientific theory is one that can make predictions about future experiments

# Model Learning

- Future data are (we assume) statistically independent of the data we have to construct our model from
  - But: we assume that they come from the same distribution
- Our approach is to simulate future data: hold out some of the available data from the model building (training) process
  - After training, we then use this *test data set* to measure the difference between model predictions and truth

# But is it that simple?

# But is it that simple?

There is typically more than one model

- Different model forms / training procedures
- Different hyper-parameters
  - Learning rates, kernel sizes ...

There could be \*many\* such choices (especially in the hyper-parameters)

# One possible solution...

Pick the model form and hyper-parameters with the highest test set performance

# One possible solution...

Pick the model form and hyper-parameters with the highest test set performance

- Because we are using the test set data to make this choice, we only know how the selected model will perform on \*this\* test data set...
  - It does not tell us about the future!
- Another take: the choice of “best” model (i.e., **model selection**) is another part of the model learning process
  - If the test set is about simulating future experience, then we should not use it for model selection, either

# Training Set for Model Selection

What about using training set performance for model selection?

# Training Set for Model Selection

What about using training set performance for model selection?

- We are back to our overfitting problem



# A Step Back to the Science Side...

We are often wanting to answer the question: what is the best model form or learning algorithm?

- Another way to look at it: I hypothesize that my algorithm is better than your algorithm
- We assume already the “best” choice for hyper-parameters for each one
- Typically the number of model forms/algorithms is much smaller than the number of hyper-parameter choices

We will separate these questions in the learning and testing procedure

# Model Learning and Selection Solution

- **Training data set:** use to choose model parameters
- **Validation data set:** for a give model form / algorithm, used to select the best hyper-parameters
- **Test data set:** use to compare form / algorithm

These different data sets must be statistically independent from one-another

# Another Dimension

Model construction and evaluation is a statistical process

- Variations in the data that are available
- Some learning algorithms make random decisions

# Another Dimension

Model construction and evaluation is a statistical process

- Variations in the data that are available
- Some learning algorithms make random decisions

We would like to have something more general than “this is the best choice for this model form / algorithm and this data”

# Dealing with the Statistical Nature of Learning

Approach:

- For a given model form and parameter choices, don't construct a single model: construct  $N$  of them
- Measure performance for all  $N$
- When comparing two different model forms or parameter sets, we can now ask a statistical question: are the performance distributions statistically different from one another?

# Dealing with the Statistical Nature of Learning

Approach:

- For many hypothesis test types, we need to assume independence of each of the  $N$  performance measures
- Technically, this means that the training/validation/test data sets must be statistically independent from one-another
- But: this means that we need  $N$  times more data

# Dealing with the Statistical Nature of Learning: Practice

Often, gathering more data is very expensive

- Instead, let's be clever in how we select our training/validation/test data

# N-Fold Cross-Validation

Approach presented in chapter 2:

- Cut your data into two pieces: test data set and “other”
- Cut the “other” into N separate folds
- Construct N models



# N-Fold Cross-Validation

- Construct N models:
  - Model 0: folds [0, 1, ... N-2] for training; fold N-1 for validation
  - Model 1: folds [1, 2, ... N-1] for training; fold 0 for validation
  - ....
- Select model hyper-parameters based on average validation set performance

# N-Fold Cross-Validation

- Use test data set to measure performance of all  $N$  models for the selected hyper-parameters
- Use mean of performance across the  $N$  to compare model forms

# Single Test Set Problem

- The  $N$  performance measures are not independent of one-another
- Our typical hypothesis testing methods will not apply here

# Alternative N-Fold Cross-Validation

- Cut full data set into  $N$  folds
- Construct  $N$  models:
  - Model 0: folds  $[0, 1, \dots, N-3]$  for training; fold  $N-2$  for validation; fold  $N-1$  for testing
  - Model 1: folds  $[1, 2, \dots, N-2]$  for training; fold  $N-1$  for validation; fold 0 for testing
  - ....
- Testing folds are independent of one-another. Hence, performance metrics are independent (somewhat)

# Alternative N-Fold Cross-Validation

- Use validation folds for hyper-parameter selection
- Only after hyper-parameters are chosen, examine test set performance
- Use test set performance to compare model forms / algorithms

# The Right Choice?

Because my typical use case is comparing multiple model forms, the latter is the proper way to proceed for my work

# Yet Another Dimension: Hyper-Parameter Selection

Two possible approaches using the validation data set:

- For each model, pick the hyper-parameters that maximize its validation performance
- Pick the hyper-parameters that maximize the average validation performance

Latter tends to give more stable results





# Classifiers

# Classifiers

Given some example, which discrete case does it belong to?

# Classifiers

## Different types of classifiers

- Some directly emit the class
  - Example: in some decision trees, a leaf is associated with a specific class
- Many classifier types represent an intermediate score
  - Decision about the class is a function of the score (or scores)
  - In particular, we will have some decision boundary (a threshold) that distinguishes between one class and the other
  - How do we choose this threshold?

