# Representing Data

## CS/DSA 5970: Machine Learning Practice

# Connecting Real World Data to our ML Tools

Often have a huge disconnect between the two.  Our ML tools often rely on:

- Well-defined formatting of the data
- Cut into distinct ***examples***.  Each example:
  - List of property values.  Most often assume each example consists of the same properties.
  - Label / expected output value (for supervised problems)

# Connecting Real World Data to our ML Tools

(cont) Our ML tools often assume:

- Properties are numerical
- Statistical independence between the different examples
- All examples are drawn from the same statistical distribution

# Connecting Real World Data to our ML Tools

Real world data can:

- Be weakly formatted
- Properties can be enumerated types (e.g., strings such as “circle”, “square”)
- Values can be incorrect
- Values can be missing
- Different examples can have different properties
- Distribution that we draw examples from can be changing in time

# Connecting Real World Data to our ML Tools

Transforming the raw data to a well-formatted form is a key first step:

- This step can take much of our project time, depending on the form of the data
- How careful we are in taking this step can dramatically affect everything else we do
- As a byproduct of this step, it is important to really understand the nature of your data

# Roadmap

- Pandas package
  - Importing data from standard formats
  - Data massaging
- Numpy package
  - Efficient representation of numerical data
- Matplotlib package
  - Matlab-like visualization package

# 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

# Classes Provided by Pandas

Two primary Python classes:

- Series: 1D data
  - Indexed by integer location in the array or by some index variable (index values can be numerical or strings)

- DataFrame: 2D data
  - Each dimension indexed by integer index or other index variable
  - Most common for us: examples (rows) x features (columns)

# Some Useful DataFrame Operations

- Data exploration:
  - Show row / column index names
  - Compute statistics for individual columns
- Create a new DataFrame that contains a subset of the rows and/or columns
- Remove or repair rows and/or columns that contain invalid data
- Export data to a numpy array for use with ML methods

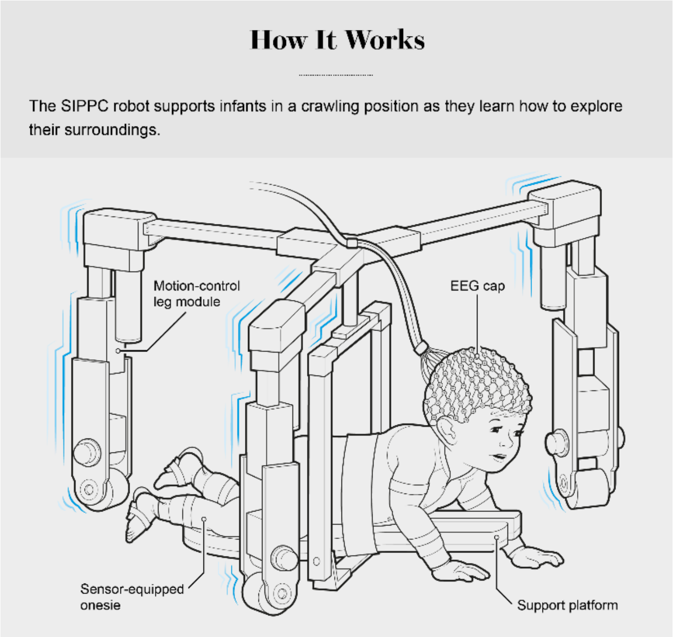
# Numpy

Numerical methods package

- Representation of vectors, matrices, tensors
  – Vector: yet another way of representing a list of numbers
- Implementation of many linear algebra type operations
  – Computing matrix inverses, Singular Value Decomposition …
- Basis for many ML packages, including Scikit-Learn

# Real-Time Activity Recognition for Assistive Robotics

OU Crawling Assistant
(Kolobe, Fagg, Miller, Ding)




Scientific American (Oct 2016)

# Infants Learning to Crawl

- Learning to crawl is in part a reinforcement learning process:
  - Initially: making novel things happen (such as the body rolling or shifting a bit) is rewarding
  - Eventually: it becomes rewarding to grasp toys (or car keys)
- These rewards are important:
  - Practice many types of motor skills
  - Drives the development of spatial skills

# Infants at Risk for Cerebral Palsy

- Initial exploratory movements do not result in interesting things happening
- These infants show a dramatic delay in the onset of crawling
- This impacts the learning of other motor skills & the development of spatial skills

# SIPPC Crawling Assistant

6-Axis Load Cell

Wide-Angle Cameras

EEG Head Net

Vertical Lifts

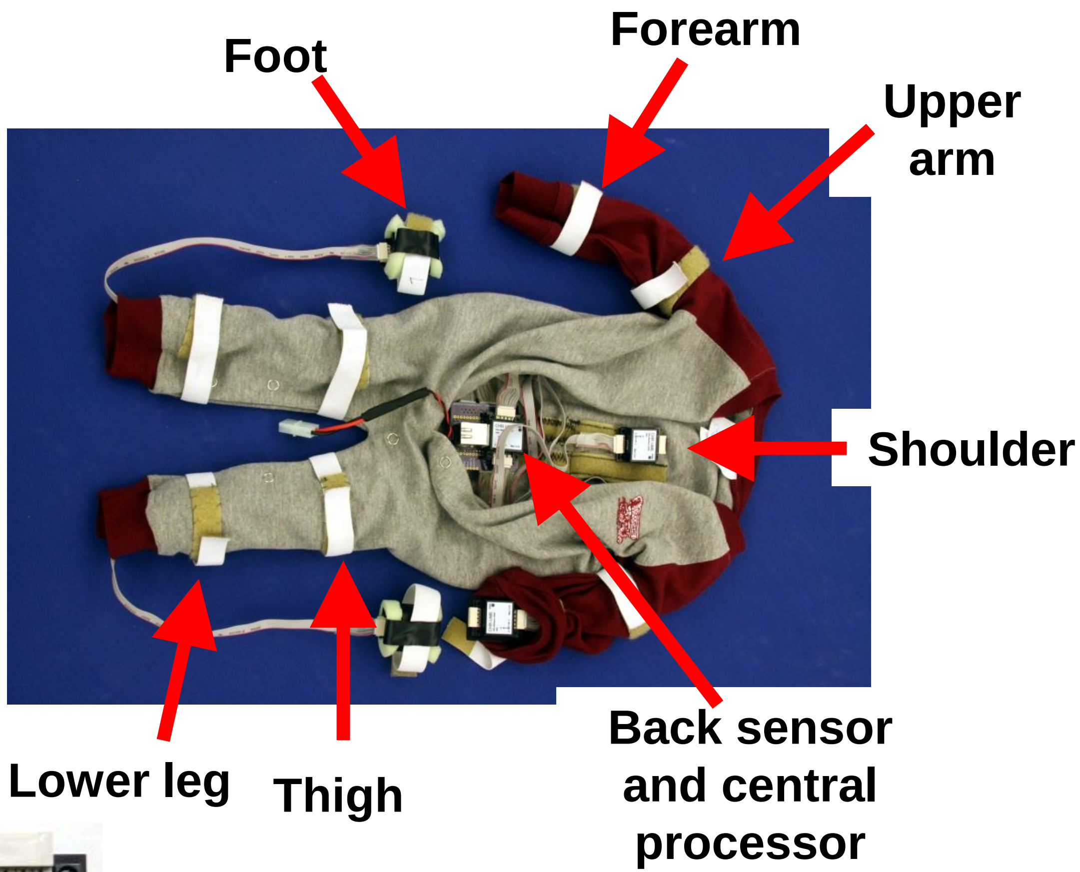
Infant Support

Covered Omni-Wheels

# 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)

# 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

# Machine Learning Questions

- Predict robot motion from kinematic data
- Predict visual attention from kinematic and robot data
- Predict limb motion from EEG data
- Predict visual attention from EEG data
- …

# Introduction to Pandas

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# Pandas Roadmap

- Importing data from Comma Separated Values (CVS) file
- Exploring data
- Indexing rows and columns

# Pandas

- Live example

# Pandas: Basic Plotting

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- Live example

# Introduction to Numpy

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# Numpy Rodmap

- Transforming Pandas data to a Numpy matrix
- Indexing Numpy matrices
- Combining vectors to create a matrix

- Live example

# Visualization with Matplotlib

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# Matplotlib Roadmap

- Creating temporal figures
- Creating scatter plots
- Tuning the display of figure elements
- Subplots
- Repairing a Pandas dataset & visualizing the results

- Live example

# Pipelines

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# Pipelines

- Data processing often involves multiple computational steps, only some of which involve ML
- The Scikit-Learn Pipeline class provides a clean interface for expressing these steps
  - Each step (or pipeline element) is implemented by a class that adheres to a standard interface
  - This allows us to mix-and-match elements for different purposes

# Flavors of Pipeline Element Classes

A pipeline element class is some combination of:

- Estimator
- Transformer
- Predictor

# Flavors of Pipeline Element Classes

Estimator: given a dataset, compute some measure or some model parameters

- Implements the fit() method
  - Takes as input one or two datasets (input data & desired output)
- Our ML methods are estimators

# Flavors of Pipeline Element Classes

Transformer: modifies a dataset in some way

- Implements the transform() method
  - Takes as input one dataset
  - Returns a dataset
- Transformers can be used to clean a dataset before it is used by a ML method

# Flavors of Pipeline Element Classes

Predictor: predicts some quantity given a dataset

- Implements the predict() method
  - Takes as input one dataset and returns a different dataset
- Implements a score() method that evaluates a prediction
  - Takes as input an input dataset and an expected output dataset
  - Returns a score

# Pipeline Notes

- Pipeline elements are classes in and of themselves
- The Pipeline class is also a pipeline elements
  - So, we can nest pipelines!
- Python classes can inherit from multiple classes
  - An element can be both an Estimator and a Predictor
- Datasets are generally Pandas objects or Numpy tensors
  - A particular pipeline element will use only one type as an input and one type as an output

- Live example

# Creating Pipeline Elements

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- Live example

# Creating Pipeline Element Classes

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# Pipeline Example: Computing Derivatives

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# Computing Derivatives

Numerical differentiation of a timeseries **x**:

- For each time t:

$$\dot{x}[t] \approx \frac{x[t+1] - x[t]}{\Delta t}$$

- Often will want to include some filtering to address the discrete nature of the data (though we won't do this here)

- Live example

# Pipeline Example: Linear Imputer

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# Linear Imputer

For our implementation: we will take advantage of the DataFrame.interpolate() method

- Live example

# Pipeline Example: Building a New Pipeline

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- Live example

# Representing Categorical Data

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# Handling Categorical Data

- Discrete, finite set of values
  - Most often the different values are strings or symbols
  - Also known as an ***enumerated type***
- Most ML algorithms only address numerical data, so need some way of transforming from categorical values to some numerical representation

# Handling Categorical Data

Often done in stages:

- Identify the set of possible categorical values
- Transform these values into an integer index
  - Order is arbitrary
- Transform the integer index into a ***1-hot encoding***
  - Array of bits: one bit per possible index value
  - For a given categorical value, only one bit is one and all others are zeros
- Different from book: use OneHotEncoder to do all of this!

- Live example

# Example: Adding Data to a DataFrame

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# Example: Adding Data to a DataFrame

Our example:

- Create a discrete label as a function of Z
- Convert discrete label to a 1-Hot Encoding
- Add these columns to the original DataFrame

- Live example