twiml

AI Enterprise Workflow Study Group

Course 2, Week 1

3/7/2020

Agenda

- Check in
- C2W1 key concepts
- Discussion
- Next steps

Course & Study Group Schedule

AI Enterprise Workflow Study Group		
Session	**Topic**	**Date**
Overview Webinar	Webinar with instructor, Ray Lopez	15-Feb
Course 1 Week 1	Course intro	22-Feb
Course 1 Week 2	Data ingestion, cleaning, parsing, assembly	29-Feb
Course 2 Week 1	Exploratory data analysis & visualization	7-Mar
Course 2 Week 2	Estimation and NHT	14-Mar
Course 3 Week 1	Data transformation and feature engineering	21-Mar
Course 3 Week 2	Pattern recognition and data mining best practices	28-Mar
Course 4 Week 1	Model evaluation and performance metrics	4-Apr
Course 4 Week 2	Building machine learning and deep learning models	11-Apr
Course 5 Week 1	Deploying models	18-Apr
Course 5 Week 2	Deploying models using Spark	25-Apr
Course 6 Week 1	Feedback loops and monitoring	2-May
Course 6 Week 2	Hands on with OpenScale and Kubernetes	9-May
Course 6 Week 3	Captsone project week 1	16-May
Course 6 Week 4	Captsone project week 2	23-May

Course 2 Week 1 learning objectives

1. Explain the principal steps in exploratory data analysis
2. Explain the use case for Python tools (pandas, matplotlib, and Jupyter) in EDA
3. Describe strategies for dealing with missing data
4. Explain the role of communication in EDA

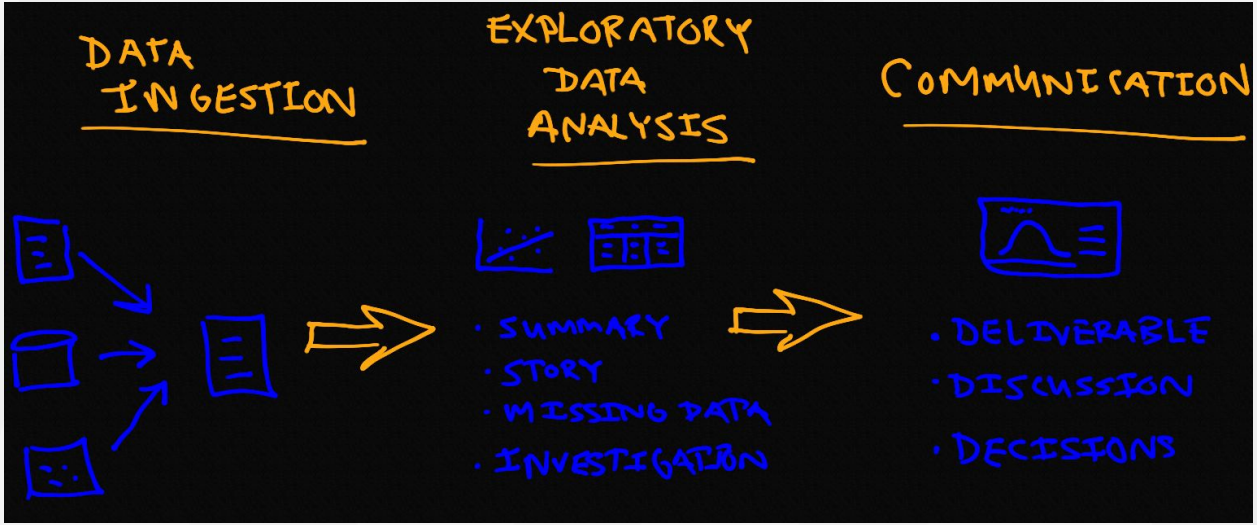
Key concepts

- Exploratory Data Analysis
  - EDA Process
  - Tools
  - Summarizing Data
- Missing Data
  - Types
  - Ways to Deal With
  - Imputation Strategies

Exploratory Data Analysis

- Exploratory vs Confirmatory
- Sometimes thoughtful EDA & visualization can reveal solution to problem such that models aren’t required.
- Challenge: Many options in how data can be visualized and results communicated

EDA Process


DATA INGESTION
EXPLORATORY DATA ANALYSIS
COMMUNICATION
· SUMMARY
· STORY
· MISSING DATA
· INVESTIGATION
· DELIVERABLE
· DISCUSSION
· DECISIONS

EDA Process Example

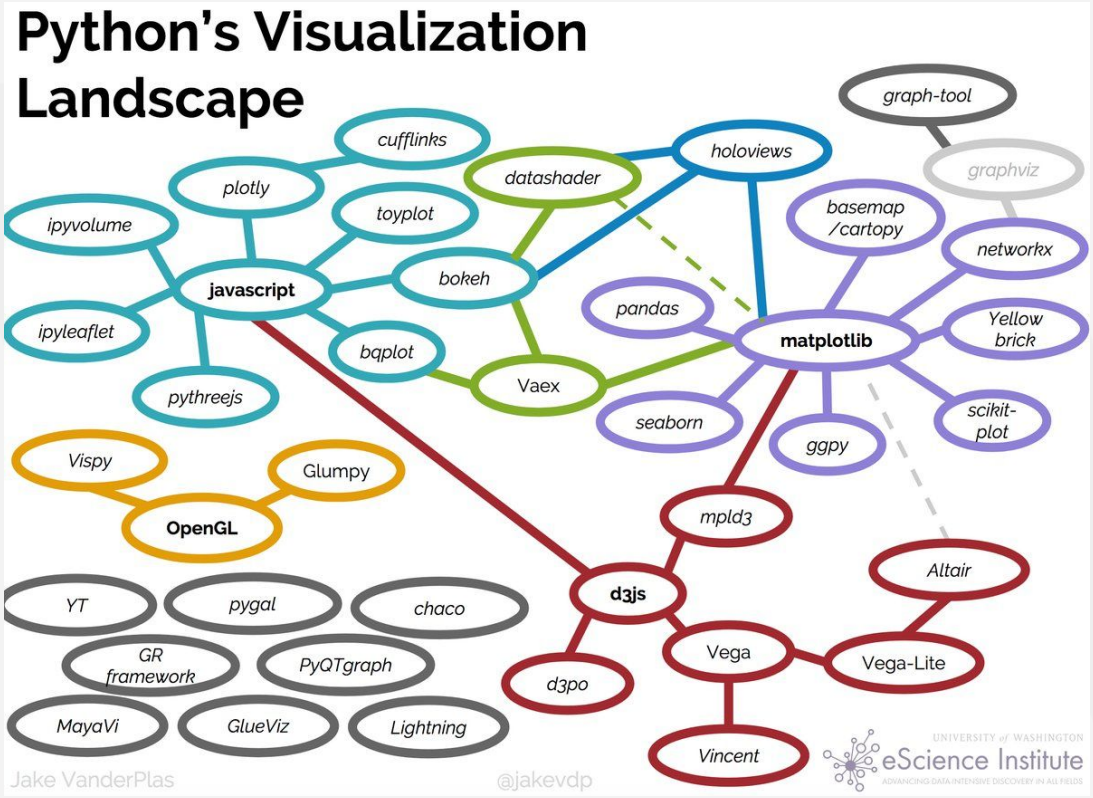
- Load data into pandas, NumPy or another similar tool and summarize the data
- Use tables, text and visualizations to tell the story that relates the business opportunity to the data
- Identify a strategy to deal with missing values
- Investigate the data and underlying business scenario with visualizations and hypothesis testing
- Communicate your findings

Communication

Not just results, also:

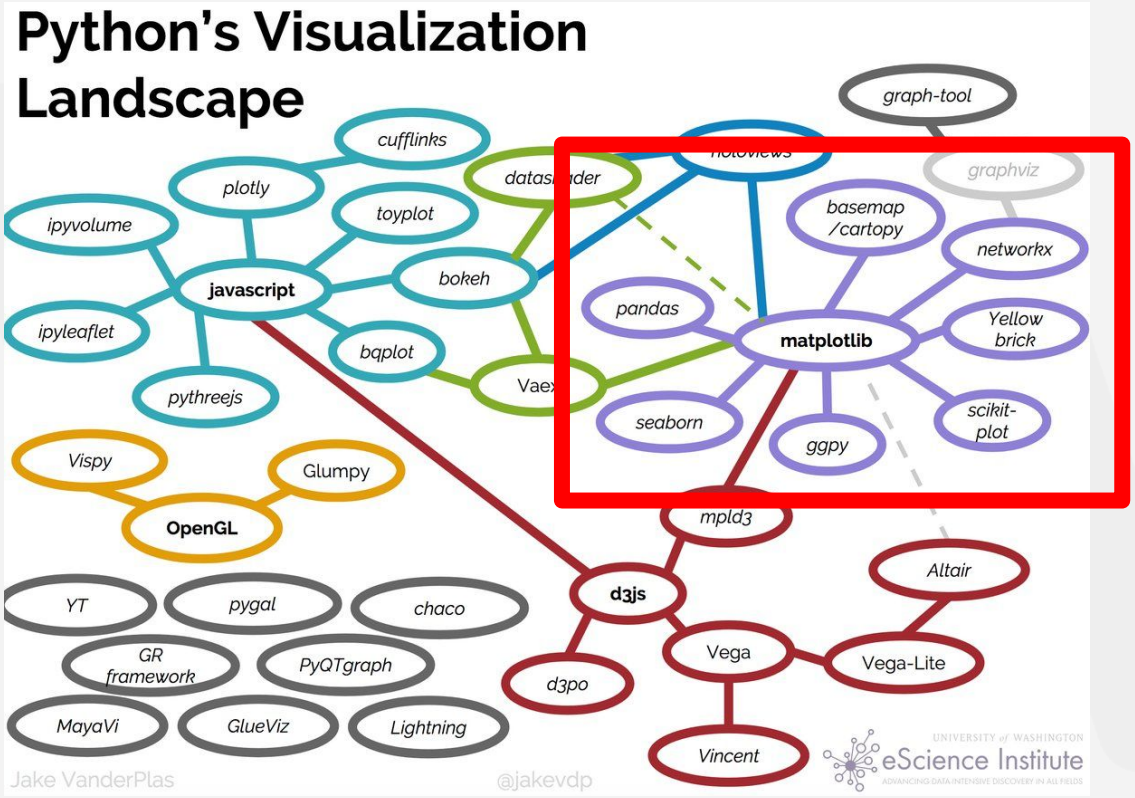
- What you have done
- What you are doing
- What you plan to do

Tools



https://www.anaconda.com/python-data-visualization-2018-why-so-many-libraries/

Tools



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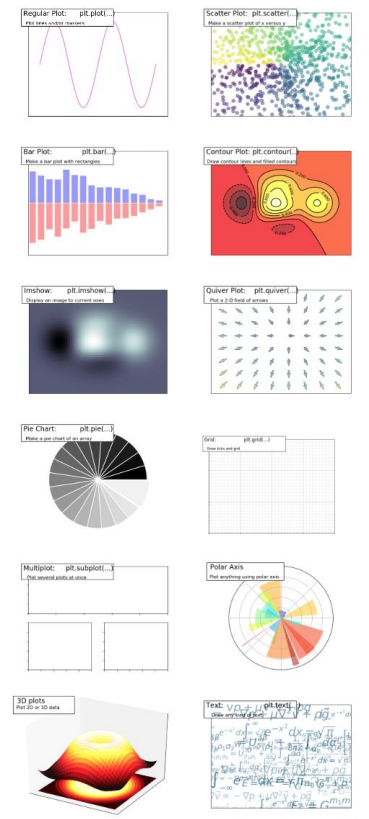
Tips

- Keep plots quick and dirty
- Emphasis is identifying and communicating insights
- Not meant to be long term dashboards
- Keep codebase separate from your visualization notebook. Code should exist as separate files, in part to ensure version control and collaboration.
- Ok to get through projects via copy/paste, but very helpful to dig into the docs to see what's possible and understand how all the pieces fit together.



Summarizing Data

- Use groupby and pivot_table to summarize data
- Discretization for continuous data: qcut() & cut()

Types of Missing Data

- Missing Completely at Random (MCAR)
- Missing at Random (MAR)
  - Some dependence on missing value e.g gender bias
  - Models can be used to impute missing values
- Missing Not at Random (MNAR)
  - Missing data depend on unmeasured or unknown variables

Dealing with Missing Data

- Ignore
- Complete Case Analysis
  - Impact depends on category of missingness
  - Rows: df.dropna()
  - Columns: df.dropna(axis='columns') // feature engineering
- Imputation
- Empathize - Try to get at the root of what's causing missing values

Imputation

Imputation: Replace missing data with substituted values

- Bayesian Imputation
- Multiple imputation

Choose strategy based on type of data:

- Categorical Data: Treat missing data as a category in categorical data.
- Numerical Data: Better to use imputation technique. Can track w new column.

Imputation strategies decided by evaluating models on hold-out set

“reconsider your imputation methods once you get to the back-and-forth between the feature engineering and modeling phases of the project”