ECBS 5148 Data Architecture for Analysts

Individual Assignment

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Pump it Up: Data Mining the Water Table

Goals

I want to participate in DrivenData's[1] data science challenge that is to build a predictive model for dysfunctional water pumps in Tanzania, Africa. DrivenData provides a dataset split into two parts: 1) features and 2) labels. My goal is to clean and enrich the data with further attributes to provide a strong basis for my future predictive models. The performance of my models will be evaluated on a test set for which I only have the features but not the labels. I will upload my predictions to DrivenData's server which will evaluate my overall results.

Data Sources

The Pump it Up challenge provides a dataset of 57 seven attributes. I have already explored this dataset for my Data Visualization assignment and I concluded it to be very messy. The labels are provided separately but can be joined one-to-one to the train features. In addition to that, we also have the test attributes.

I want to do some advanced feature engineering, in this case calculating distances for a particular water pump station. I want to calculate what is the closest region center (capital) to a pump location. The reason for doing so is that I suspect water pumps may be harder to maintain further away from the capital of region due to the lack of available resources, mainly expertise and pump parts.

For this, I will need to have data on the regions and their centers. I am going to scrape this data from this website: URL which lists the regions and their capitals along other -for this exercise irrelevant- attributes.

To calculate the distance between a water station and the closest city center, I am going to use the HERE API. First, I will need to scrape the coordinates of the capitals and then using the two coordinates, I am going to be able to fetch distance data from the API. Since this API is super fast, and free subscribers are allowed to make 250,000 requests monthly, I will query distances between a water station and every capital. Then, filtering for the shortest distance will be the capital closest to a specific station.

To enable my model to also account for differences in income, I will again scrape data. In this case, I will scrape Wikipedia to get the regional GDP per capita (of 2016) data.

Table previews

Features

ID	owner	gps_height	lon	lat	region	basin	water_quality	...
1111	XY	1335	37.202	-3.22	Kilimanjaro	Pangani	soft	

[1] Here you can find out more about the challenge: https://www.drivendata.org/competitions/7/pump-it-up-data-mining-the-water-table/

The features data table contains the information of an inspection at a specific date. It records the date and the -mostly constant – attributes of the water station. This table is redundant, thus, it will be normalized.

Labels

ID	status_group
1111	functional
2222	non functional
3333	functional but needs repair

The labels record the inspection result.

GDP

Region	GDP per capita in USD (PPP)
Dar es Salaam	4,415
Mbeya	4,236

GDP contains regional income date for 2016. Since inspections range between 2010 and 2012 I think this data will do good enough for my data product.

Capitals and coordinates

Region	Capital	Latitude	Longitude
Arusha	Arusha	-3.377580	36.687684
Dar es Salaam	Dar es Salaam	-6.805026	39.219950

The coordinates for each capital will be scraped and joined to the capitals table.

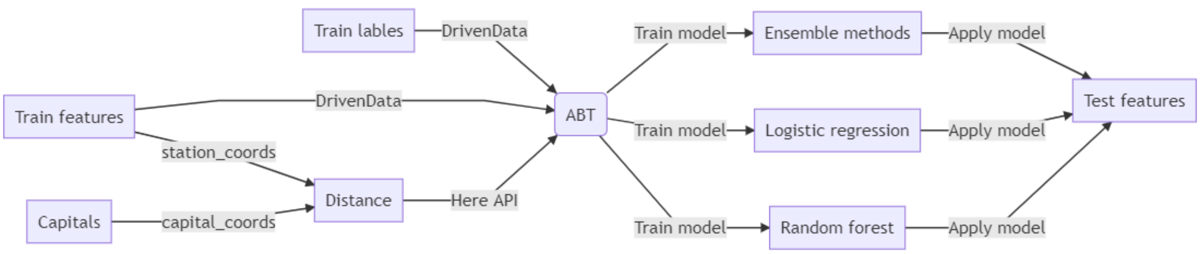
Distances

wpt_name	wpt_lat	wpt_long	capital	capital_lat	capital_long	dist(km)
XY	-3.22	37.202	Dar es Salaam	-6.805026	39.219950	569

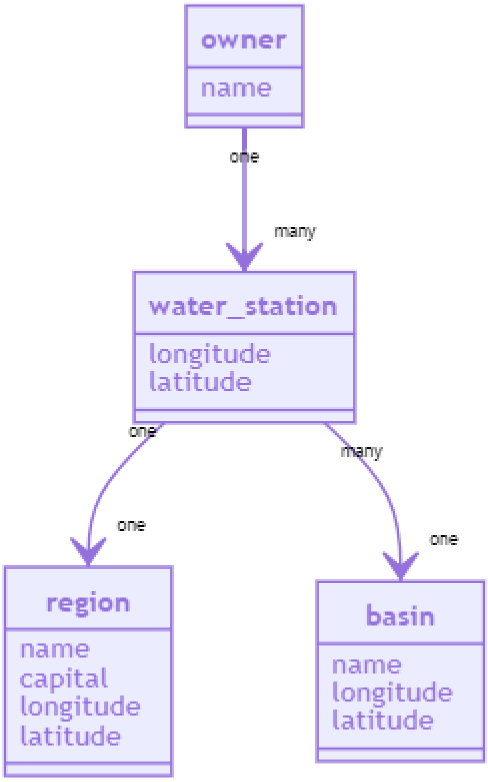
The distances table contains all water stations and capital combinations. There will be 5000 (No. station) * 22 (No. region) = 110.000 records in this table.

Conceptual model

ABT means Analytical Base Table which will be a single table ready-for-analysis. In other words, this will be my data product.



Entity Relationship Model



Technical and Legal Constraints

I will only use publicly available data and open source software tools. I will use, in particular, Python, SQLite, R and OpenRefine for data-related purposes and use Frictionless Data and Mermaid for documenting. I will work on my laptop, so data should fit into that.

Since the `core` dataset (DrivenData) is publicly available and I found no information indicating any legal constraint, I think I can use this dataset as it is. The robots.txt may prohibit me access to the material I am planning scrape, in which case I will have to look for other sources.

Learning Outcomes Demonstrated

I am planning to demonstrate the acquired skills of this course through the following examples, grouped by class topic:

Data Architecture

Separate important from unimportant features: the labels data contains also non-essential attributes which will be dropped

Represent a mental model visually: demonstrated in this document, at the ERD section

Create diagrams with Mermaid or other tool: demonstrated in this document, at the ERD section

Data Modeling

Recognize tidy data: the data downloaded from DrivenData is not tidy but the final dataset will be

Create logical model for simple relational data and represent it with Entity-Relation Diagrams: demonstrated in this document, at the ERD section

Create and query a simple database in SQLite or other RDBMS: data will be stored in SQLite

Understand and apply normal forms 1-3 to simple relational data: normalization 1-3 will be applied on the data product

Model many-to-one relationships: conceptually demonstrated in this document, at the ERD section and will be implemented in SQLite

Data Structures

Build a binary tree from simple ordered data: data tables will be indexed in SQLlite

Compare different data structures: TBA

Data Serialization

Compare popular serialization formats fixed width, CSV, JSON, XML, YAML, JSONlines, Parquet: I/O and memory usage will be compared between CSV and Parquet for the biggest, labels dataset.

Explain the tradeoffs in data serialization: the results of the former will be elaborated

Data Quality

Use string functions in OpenRefine or other tool to normalize text data: categorical data are messy, especially the name of the owners

Save, edit and replay changes in OpenRefine on different datasets: OpenRefine will be used for cleaning purposes and the steps implemented will be saved in json for transparency and reproducibility.

Data Integration

Understand basic robots.txt structure: this will be inspected before scraping data

Use wget, curl or other programmatic tool to download data from the web: websites will be scraped

Create a Data Package to share data and metadata together: the final data product will be documented this way