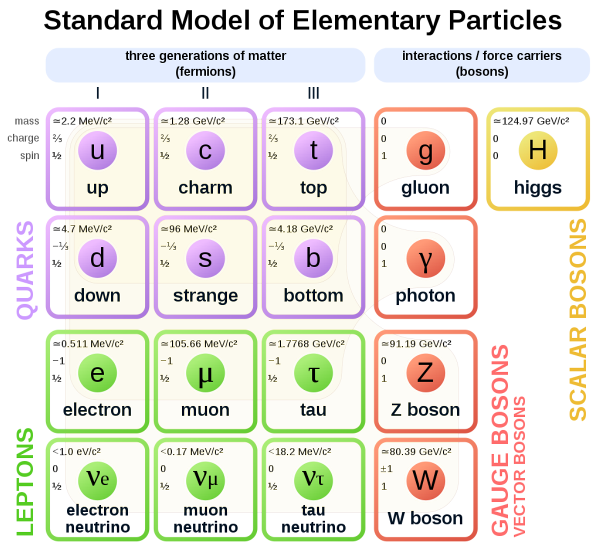
Project Proposal: Flavors of Physics, The Strange D Meson Decay

Domain Background

This project is a particle physics problem. Its name is inspired by what physicists call "flavor", the species of an elementary particle. The Standard Model of particle physics is a well established theory that explains the properties of fundamental particles and their interactions, describing the "flavor" of each particle. As mentioned in Charlotte Louise Mary Wallace CERN Thesis, the Standard Model theory has been tested by multiple experiments, but despite its successes, it is still incomplete and further research is needed.

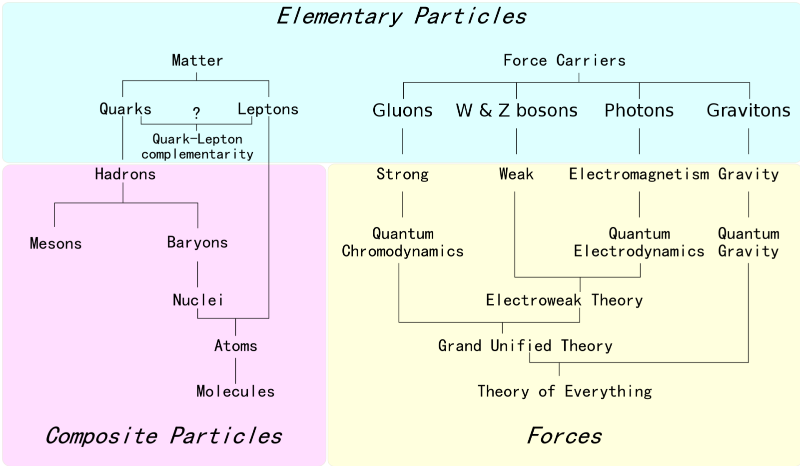
The Standard Model counts six flavors of quarks and six flavors of leptons, as shown below. "Flavor" is essentially a quantum number that characterizes the quantum state of those quarks.



The Ds decay project is influenced by a CERN kaggle competition problem about the flavors of physics. In the initial problem, scientists try to find if it is possible that the τ (*tau*) lepton to decay (transform into multiple other particles) to three μ (muon) leptons. The problem I chose however concerns the Ds meson or *strange D meson*, a composite particle that consists of one quark or one antiquark, and how often it decays into a ϕ (phi meson) and a π (pi meson or pion) based on multiple features and observations. The decay is described by the following flow:

$$D_s \rightarrow \varphi\pi$$

You can see where the meson belongs in the subatomic particles map below. The purple part describes the composite particles.



Ander's Ryd in his paper argues that the D meson decays have been a challenge, though scientists have been focused on their decays since the particle discovery. As a result the existing dataset of this project is sufficient and based on well-studied experiment observations.

Problem Statement

The problem falls into the category of binary classification problems. Based on particle collision events (that cause the $D_s \rightarrow \varphi\pi$ decays) and their properties, I am challenged to predict whether the decay we are interested in happens in a collision or not.

Datasets and Inputs

As described in the flavors of physics project, the $D_s \rightarrow \varphi\pi$ decay has a very similar topology as the *tau* decay and their datasets share almost the same features. In the *tau* decay problem, the Ds decay data is used as part of the the CERN evaluation process for that problem. This dataset will be used as the main dataset of the $D_s \rightarrow \varphi\pi$ decay problem solution.

This is a labelled dataset (the label 'signal' being '1' for decays happening (signal events) and '0' for decays not happening (background events)) to train the classifier.

- FlightDistance - Distance between Ds and PV (primary vertex, the original protons collision point).
- FlightDistanceError - Error on FlightDistance.
- LifeTime - Life time of Ds candidate.
- IP - Impact Parameter of Ds candidate.
- IPSig - Significance of Impact Parameter.
- VertexChi2 - $\chi 2$ of Ds vertex.
- dira - Cosine of the angle between the Ds momentum and line between PV and *tau* vertex.
- pt - transverse momentum of Ds.
- DOCAone - Distance of Closest Approach between p0 and p1.
- DOCAtwo - Distance of Closest Approach between p1 and p2.
- DOCAthree - Distance of Closest Approach between p0 and p2.
- IP_p0p2 - Impact parameter of the p0 and p2 pair.
- IP_p1p2 - Impact parameter of the p1 and p2 pair.
- isolationa - Track isolation variable.
- isolationb - Track isolation variable.
- isolationc - Track isolation variable.

- isolationd - Track isolation variable.
- isolatione - Track isolation variable.
- isolationf - Track isolation variable.
- iso - Track isolation variable.
- CDF1 - Cone isolation variable.
- CDF2 - Cone isolation variable.
- CDF3 - Cone isolation variable.
- ISO_SumBDT - Track isolation variable.
- p0_IsoBDT - Track isolation variable.
- p1_IsoBDT - Track isolation variable.
- p2_IsoBDT - Track isolation variable.
- p0_track_Chi2Dof - Quality of p0 muon track.
- p1_track_Chi2Dof - Quality of p1 muon track.
- p2_track_Chi2Dof - Quality of p2 muon track.
- p0_pt - Transverse momentum of p0 muon.
- p0_p - Momentum of p0 muon.
- p0_eta - Pseudorapidity of p0 muon.
- p0_IP - Impact parameter of p0 muon.
- p0_IPSig - Impact Parameter Significance of p0 muon.
- p1_pt - Transverse momentum of p1 muon.
- p1_p - Momentum of p1 muon.
- p1_eta - Pseudorapidity of p1 muon.
- p1_IP - Impact parameter of p1 muon.
- p1_IPSig - Impact Parameter Significance of p1 muon.
- p2_pt - Transverse momentum of p2 muon.
- p2_p - Momentum of p2 muon.
- p2_eta - Pseudorapidity of p2 muon.
- p2_IP - Impact parameter of p2 muon.
- p2_IPSig - Impact Parameter Significance of p2 muon.
- SPDhits - Number of hits in the SPD detector.
- min_ANNmuon - Muon identification. LHCb collaboration trains Artificial Neural Networks (ANN) from information from RICH, ECAL, HCAL, Muon system to distinguish muons from other particles. This variables denotes the minimum of the three muons ANN. min ANNmuon should not be used for training. This variable is absent in the test samples.
- signal - This is the target variable for you to predict in the test samples.

Obtain the dataset

There are three ways to get the data described above:

- I recommend to download the resampled dataset from the github repo I created for this project. I intent to use this resampled dataset, as the original is heavily imbalanced. The resampled dataset is also smaller and much more easy to manage, which makes it more suitable for this Udacity project. I made sure that the dataset have sufficient data for my analysis. If you want to get the original dataset, follow the next point.
- From kaggle, by downloading the *check_agreement.csv.zip* from here (this requires a kaggle account).

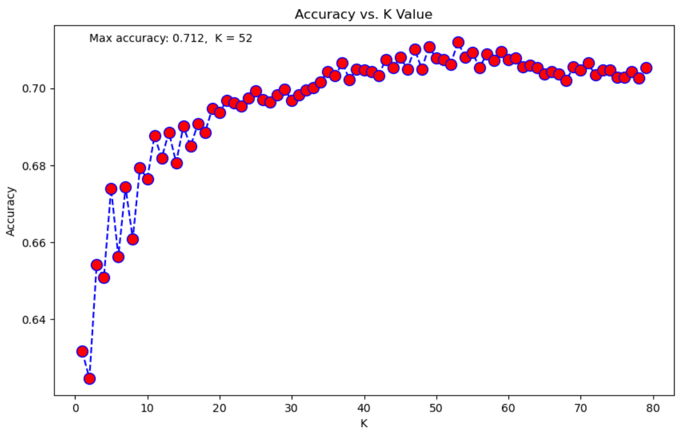
> Note that in the resampled dataset, I have dropped the "weights" feature from the original dataset, as according to the description of the dataset, is the feature used to determine if the decay happens or not based on its value, and is the one used to create the binary *signal* column. It will be not used in the solution whatsoever.

Solution Statement

This is a binary classification problem so the solution will involve a binary classifier. There is no constrain in using any classifier in particular for this family of problems. However, in the evaluation description of the kaggle competition described so far, is it mentioned that the Kolmogorov–Smirnov (KS) test is used to evaluate the differences between the classifier distribution and the true *signal* values distribution. I intent to train multiple models in combination with different data cleaning methods, but in the final solution I will only present the chosen data cleaning method and model based on evaluation from different performance metrics, including the KS test.

Benchmark Model

As a benchmark model I use a simple k-Nearest Neighbor classifier trained in the resampled data, and grid search for tuning the k hyperparameter. The benchmark model script can be found here. The execution of that script generates the following plot. The plot shows the accuracy of the kNN model for each one of the k values (from 1 to 80). The best model is the kNN model with k=52, with accuracy 71%.



Evaluation Metrics

The evaluation metric used to choose the k values of the kNN benchmark model is the `sklearn` accuracy. It is calculated by dividing the number of correct predictions by the total number of samples.

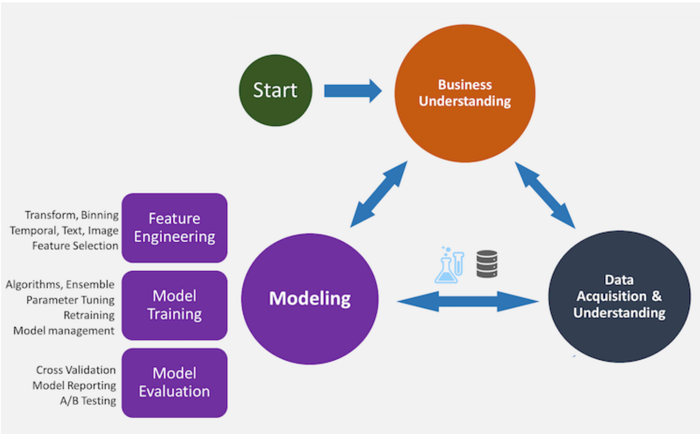
Project Design

A high level workflow for the solution approach:

1. **Understand the problem - identify the problem category**: I already know that this is a binary classification problem, which will help me choose the models to train.
2. **Data mining**: Obtain the necessary datasets for this analysis, as mentioned in the associated section of data input above.

3. **Data Visualization, Cleaning and Engineering**: Check if the data is balanced, if there are linear correlation between the features to determine which features to keep or check if the data will work better with a specific scaling. Distribution plots or even dimensionality reduction techniques may help visualize the data to have a better understanding of their shape and behavior.
4. **Model Training/Tuning**: Train a selection of binary classification algorithms, trying different data scales, different number of features and cross validation to avoid overfitting. Make use of search techniques like grid or random search to tune the hyperparameters. Models like Support Vector Machines, Stochastic Gradient Descent or XGBoost classifiers might be suitable for this problem as they can deal with multiple features efficiently.
5. **Model Evaluation**: A number of performance metrics will be used for this step. Evaluation metrics suitable for this problem might be false positive rate, false negative rate, specificity, negative predictive value, accuracy or Kolmogorov–Smirnov test.

A workflow that sums up the steps above is presented below. This workflow is part of a typical data science lifecycle, as presented here.



Why I chose this project?

I have a bachelor's degree in physics, but I haven't worked as a physicist so far. I started having an interest in data science in recent years and I am now confident enough to start utilizing my data science knowledge in solving physics problems, combining my passion for both fields. I specifically chose a particle physics project as I know that scientists at CERN often provide data to the public based on their observations, and that I would be able to find both an interesting machine learning problem and a dataset online to work with, with sufficient data for a data science analysis. I initially started working on the tau decay problem described briefly in the begging of the proposal, but the classifier predict the signal with high performance without much hyperparameters tuning due the nature of the dataset. I believe that this wouldn't help me learn as a much as a problem that would require further model improvements to get high performing results, so I switched to the Ds decay which is a similar problem with a lower benchmark performance.

Sources:

- https://en.wikipedia.org/wiki/Flavour_(particle_physics)
- https://cds.cern.ch/record/2713513?ln=en
- https://en.wikipedia.org/wiki/Standard_Model
- https://cds.cern.ch/record/2196092/files/CERN-THESIS-2016-064.pdf
- https://en.wikipedia.org/wiki/Particle_decay
- https://en.wikipedia.org/wiki/D_meson

- https://en.wikipedia.org/wiki/Phi_meson
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