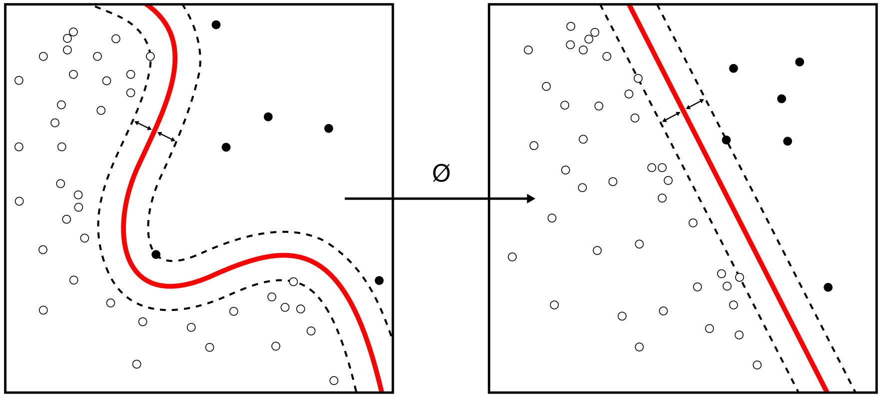
QSVM for LTIM at MCQuICC

Received Dataset

Coolant T	Fuel P	LOG(Engine rpm)	LOG(Lub oil P)	LOG(Coolant P)	lub oil T	Engine Condition
-0.7727	0.3442	0.4828	-0.2438	0.2430	0.5634	**1**
...	...	...	...	...	...	...
...	...	...	1200 rows	...	...	
...	...	...	...	...	...	...
-0.0863	-0.0622	-0.3165	-0.2442	0.5177	0.0347	**0**

Objectives

- Classify engine condition
- Use SVM for classification
- Compare QSVM with classical SVM



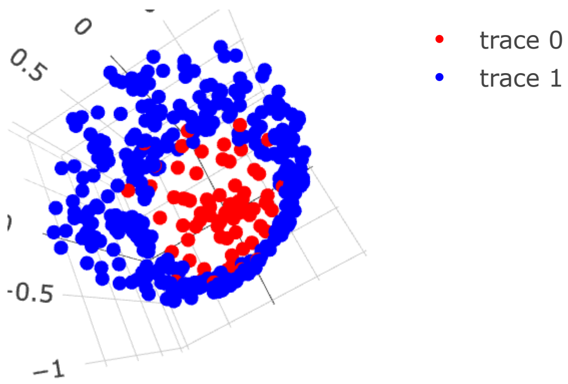
Kernel Machine

We want a more accurate curvy line for which we need to transform the feature space. This is where the kernel trick comes in.

- Go to a higher dimension
- Find a linear separator
- Project back to original space

More mathematically

- Find a feature map ϕ such that $\phi(x_i) \cdot \phi(x_j) = K(x_i, x_j)$
- Generate a kernel matrix K such that $K_{ij} = K(x_i, x_j)$
- Find all support vectors i.e $\alpha_i \because \sum \alpha_i y_i = 0$
- Find the bias b such that $y_i(\sum \alpha_i y_i K(x_i, x_j) + b) = 1$
- We can now predict $Y_{OUT} = \text{sign}(\sum \alpha_i y_i K(X_{IN}, x_j) + b)$



Two Approaches

Quantum Precomputed + Classical SGD

⚛ Quantum precomputed kernel
↓
💻 Classical SGD

Advantages

- Better feature space
- More noise resistant

Classical RBF + Annealing

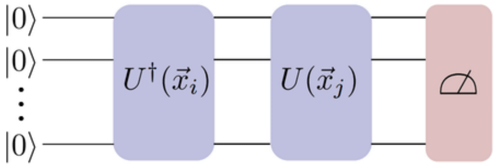
💻 Classical RBF kernel
↓
⚛ Quantum Annealing for minima

Advantages

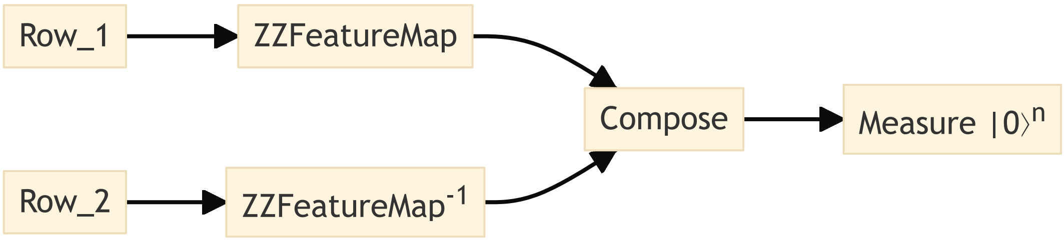
- More feasible on current hardware
- Faster

Quantum Precomputed Kernel Mechanism

- Each Pair of rows ${}^{N}C_2$ of 6 features each is fed to a quantum circuit as 12 parameters



$$\Rightarrow K_{ij} = |\langle 0|U^\dagger(\vec{x}_i)U(\vec{x}_j)|0\rangle|^2$$



Annealing Mechanism