Quantum Algorithms and Romantic Love:
Predicting Satisfaction through Personality and Partner Perceptions

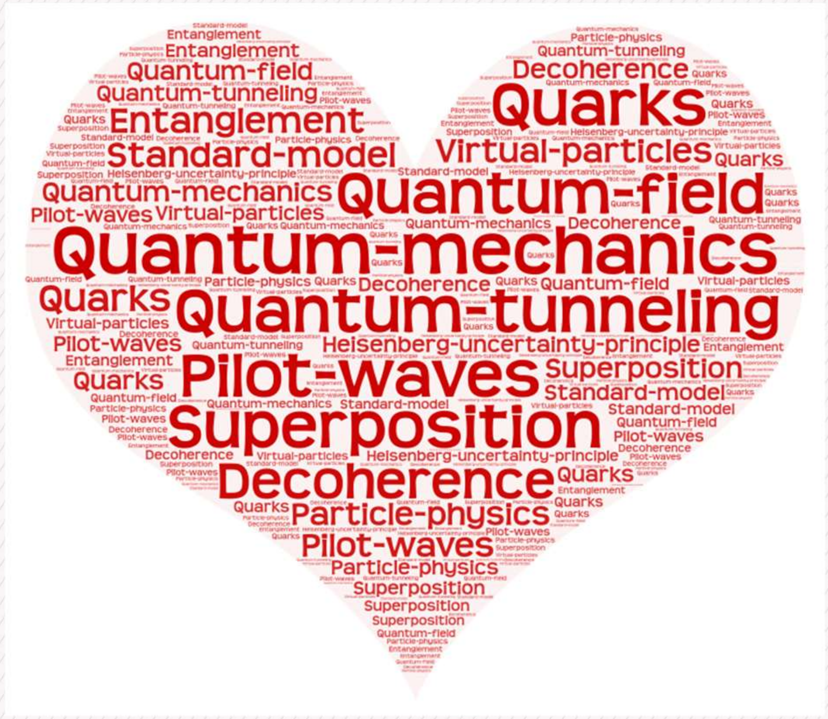
Micah Tracy—Data Science Major

Dr. Ignacio Segovia-Dominguez—Advisor

WestVirginiaUniversity.

Abstract

This project uses Qiskit to evaluate the training speed and performance of a Variational Quantum Classifier against a classical Support Vector Machine for predicting relationship satisfaction. Although the quantum model lagged in accuracy, it showed faster training in complicated cases, highlighting how quantum machine learning may become practical as hardware advances.

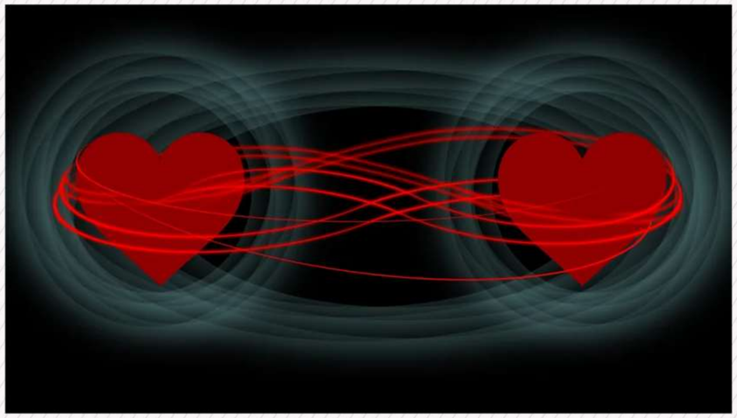


Introduction

Introduction

- Quantum computing is gaining momentum, even though the hardware still needs improvement.
- This project evaluates how well a quantum algorithm predicts romantic relationship satisfaction compared to a classical machine learning model.
- After the survey data is prepared for machine learning, both an SVM and a VQC are trained, and their accuracy and training time are compared.
- The quantum model is expected to underperform in accuracy but potentially show a speed advantage.

Background Information



- **Dataset:** Romantic Love Survey 2022, collected from 1556 people in English-speaking countries who are in romantic relationships.
- **Features:** Personality, relationship characteristics, romantic love measures, partner perceptions, and well-being.
- **Previous Studies:** Often cluster respondents into relationship "types."
- **Purpose:** Predicting an individual's satisfaction in the relationship from these factors.

Background Information

- Quantum systems can encode more information than classical systems.

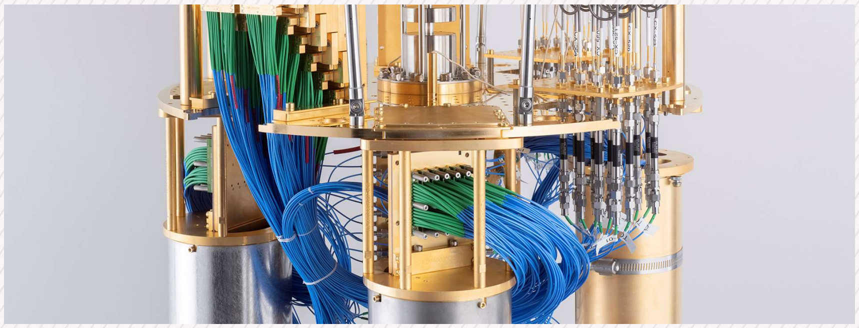
- Current hardware is highly sensitive to errors, limiting circuit size and complexity.
- Goal: fault-tolerant quantum computer.

- "[Quantum Machine Learning] explores learning algorithms that can be executed on quantum computers to accomplish specified tasks with potential advantages over classical implementations." (Du, et. Al 2025)

- IBM's Qiskit software allows users to run and simulate quantum algorithms despite limited access to real hardware.

$$\begin{pmatrix}1\\0\end{pmatrix} = |0\rangle \quad \text{and} \quad \begin{pmatrix}0\\1\end{pmatrix} = |1\rangle,$$

Quantum Standard Basis Vectors [1]



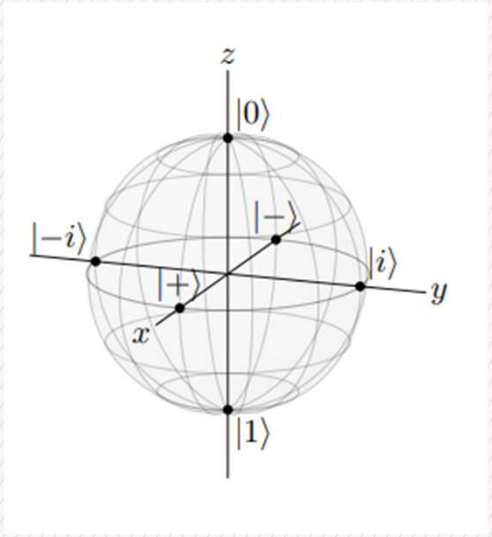
Quantum Computer [2]

Background Information

Since a qubit can be in a superposition of $|0\rangle$ and $|1\rangle$, states like these are possible.

$$|+\rangle = \frac{1}{\sqrt{2}}(|0\rangle + |1\rangle),$$
$$|-\rangle = \frac{1}{\sqrt{2}}(|0\rangle - |1\rangle),$$
$$|i\rangle = \frac{1}{\sqrt{2}}(|0\rangle + i|1\rangle),$$
$$|-i\rangle = \frac{1}{\sqrt{2}}(|0\rangle - i|1\rangle).$$

Four Common Quantum States [3]



Bloch Sphere: Visualizing States of Qubits [4]

Background Information

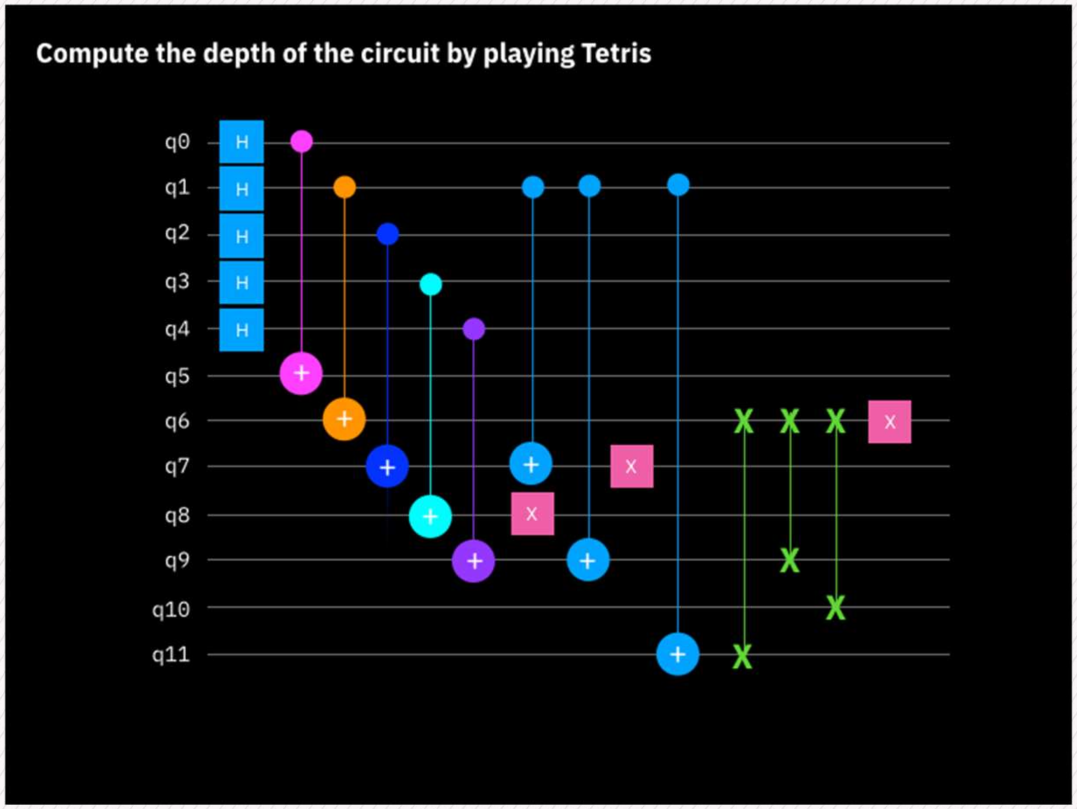
- This video shows the relationship between different quantum states as represented on the Bloch Sphere.

Bloch Sphere Visualization [5]

Hadamard Gate [6]

- The Hadamard gate is often used in quantum mathematics to distinguish between a ground state and a superposition, and vice versa.
- This allows $|+\rangle$ and $|-\rangle$ states to be discriminated perfectly.

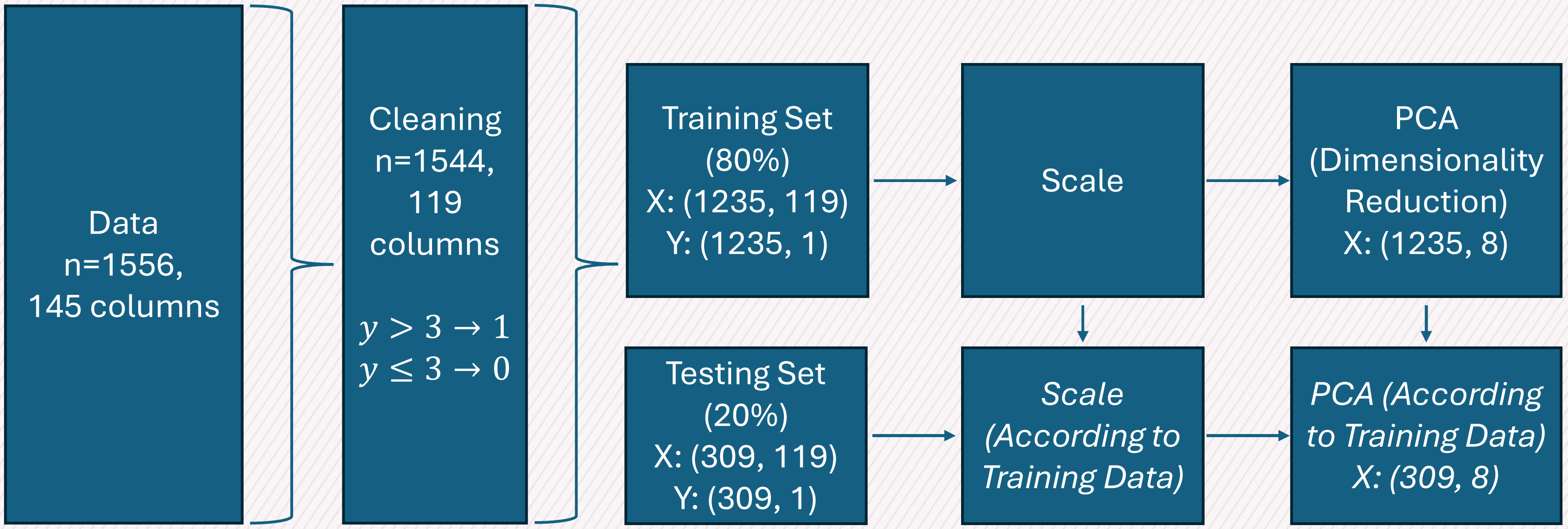
Background Information



Depth of a Circuit [7]

Methods

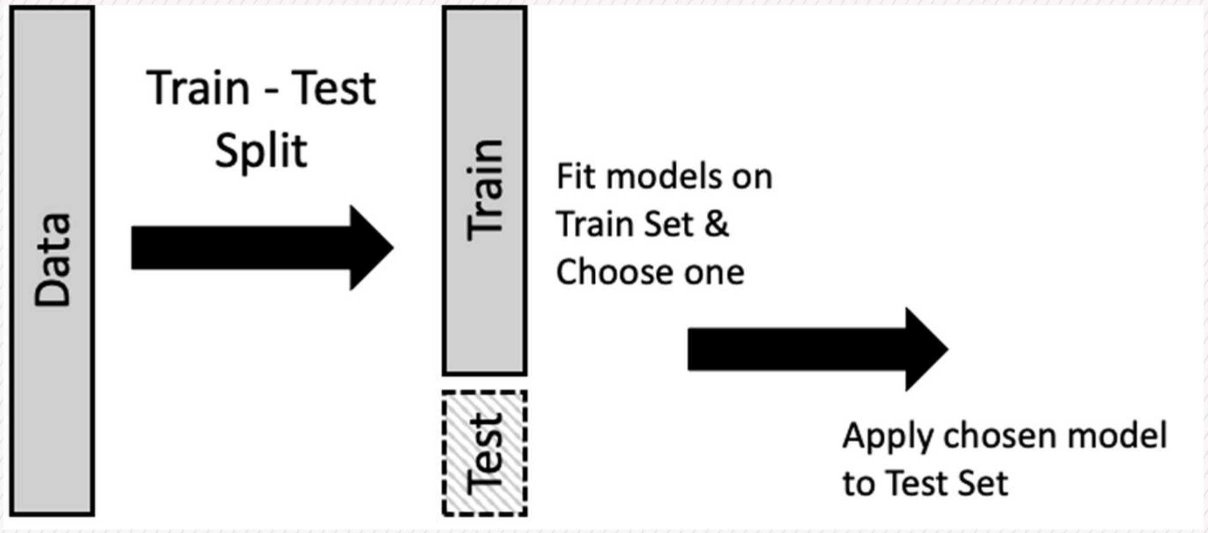
Data Pipeline: Preparation for the Models



Data n=1556, 145 columns
Cleaning n=1544, 119 columns
$y > 3 \rightarrow 1$
$y \leq 3 \rightarrow 0$
Training Set (80%) X: (1235, 119) Y: (1235, 1)
Scale
PCA (Dimensionality Reduction) X: (1235, 8)
Testing Set (20%) X: (309, 119) Y: (309, 1)
Scale (According to Training Data)
PCA (According to Training Data) X: (309, 8)

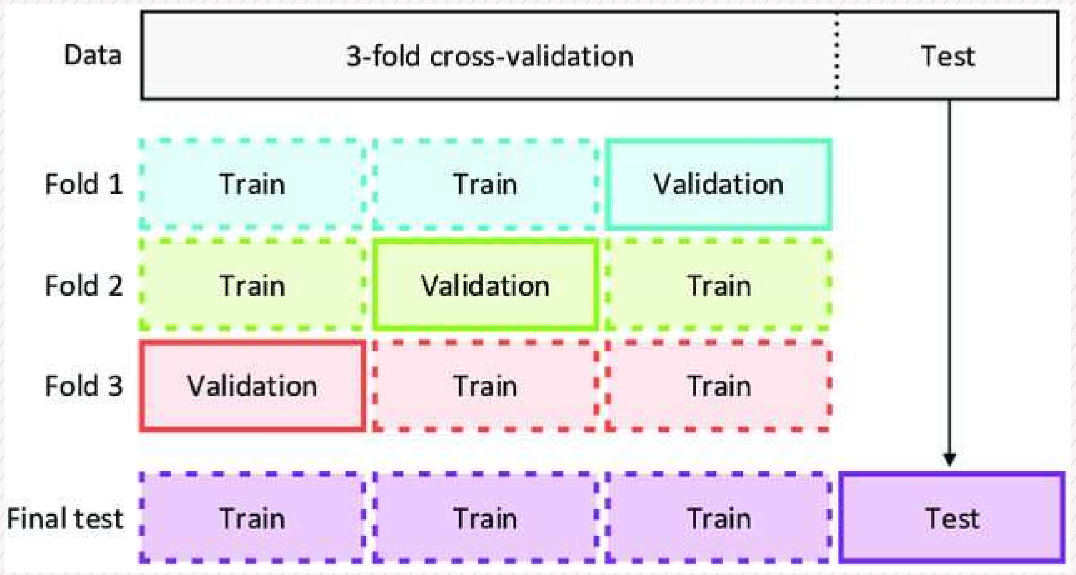
Train Test Split

- Keeps the model from overfitting.
- Ensures the model performs well on unseen data.
- The training set was used for cross-validation.


Data
Train - Test Split
Train
Test
Fit models on Train Set & Choose one
Apply chosen model to Test Set

Train Test Split Explanation [8]

Cross Validation Procedure



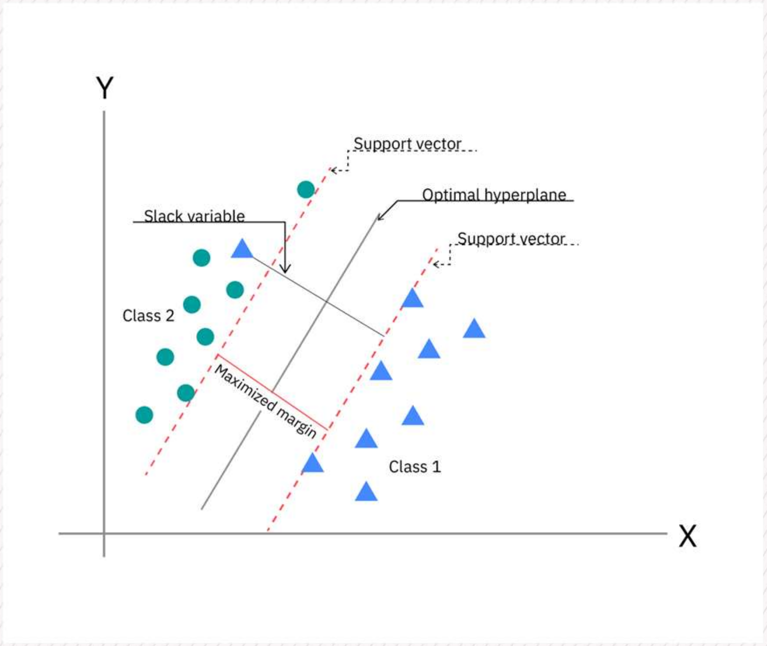
Cross Validation with Three Folds [10]

- Hyperparameters, values that control the learning process, were tuned for both models using cross-validation.
- Three splits were used.
- This is a robust way to assess the performance of different hyperparameter values.

HPCs

- Due to the significant amount of time required for the models to train, the experiment was conducted using WVU’s High Performance Computing Clusters.
- Specifically, the models were trained on the Dolly Sods cluster.
- This allowed the programs to be scheduled to run in the background, since tuning and training each model sometimes took a few hours.

Support Vector Machine



Support Vector Machine Representation [9]

- Tune hyperparameters using GridSearchCV: cross-validation using 18 combinations
  - C values: 0.1, 1, 10
  - Kernel Types: linear, poly
  - Gamma: 0.01, 0.1, 1
- Trained the SVM classifier with the best hyperparameters on the whole training set.

Variational Quantum Classifier

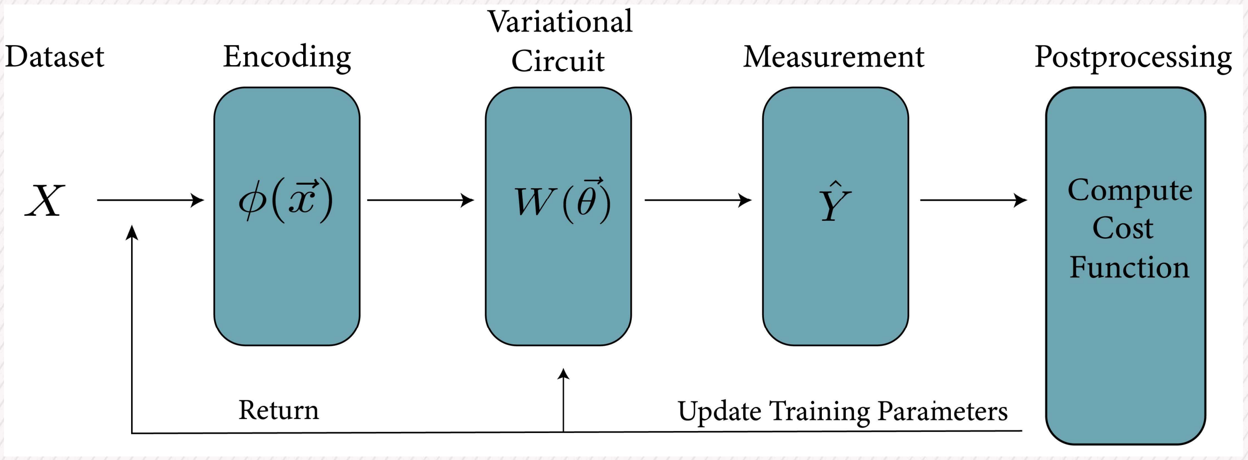
$$f_\theta(\vec{x}) = \langle 0|U^\dagger(\vec{x})W^\dagger(\theta)OW(\theta)U(\vec{x})|0\rangle$$

Function Mapping Data Vector to the Correct Category [11]

- $U(\vec{x})$ is the encoding circuit
- $W(\theta)$ is the variational (trainable) circuit block
- θ is the set of parameters that we are training
- O is an observable that is estimated
  - Not defined in the training of VQC: measured bitstrings are taken as the output of the classifier.

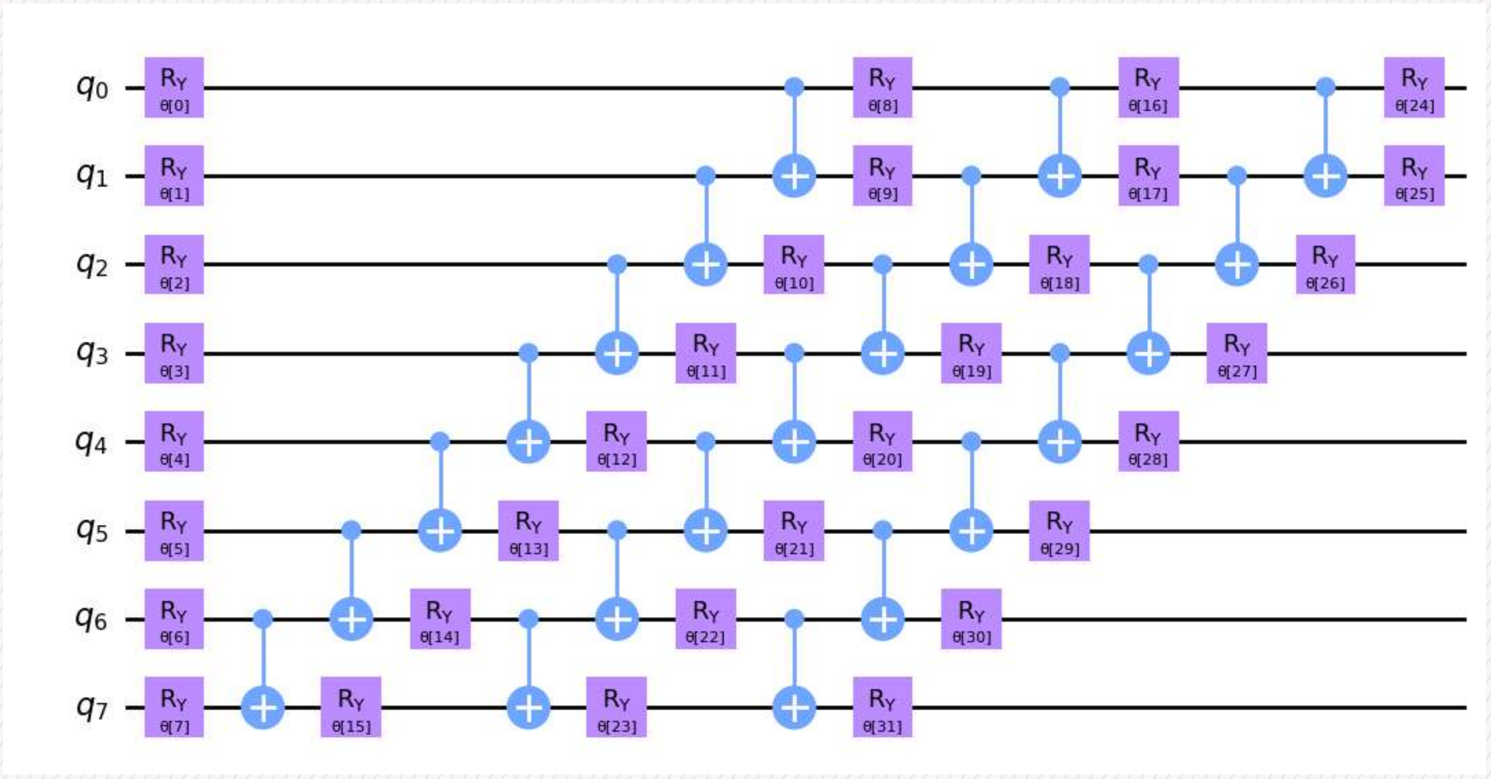
VQC

- Encoding: ZZFeatureMap
- Optimizer: COBYLA
- Loss function: Cross Entropy



Schematic Diagram of VQC Model [12]

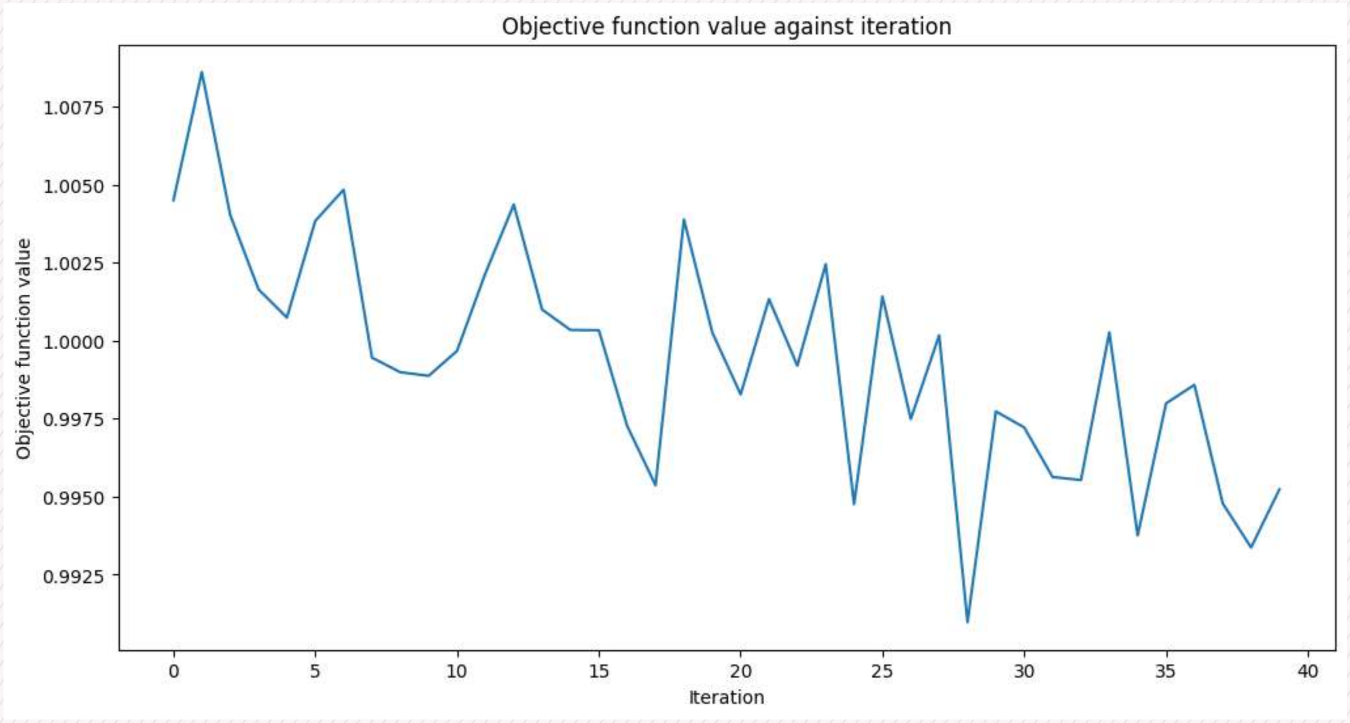
- GridSearchCV through Sklearn is not supported with Qiskit's VQC algorithm, so the best combination was found by looping through the hyperparameter combinations.
- Variational Circuit (ansatz): Options were RealAmplitudes, EfficientSU2, and ExcitationPreservation.
  - The number of repetitions (the number of copies of the entanglement layer) was also varied from 1 to 6.



An example of a RealAmplitudes ansatz with 3 repetitions.
The different θs are the values that are estimated in the model.

Results, Discussion and Conclusion

VQC Optimization



Optimization of Variational Quantum Classifier

Results

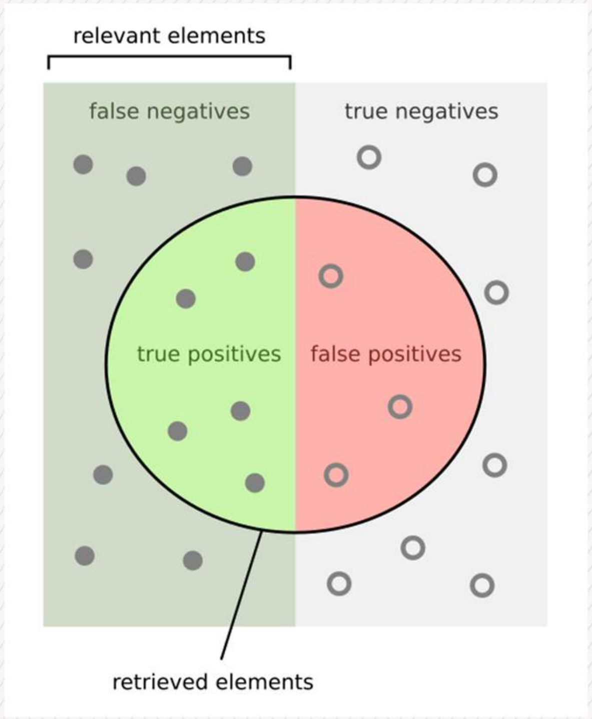
- The quantum model underperformed (~54% accuracy) compared to the classical model, which was over 90% accurate.
- The best quantum model also took longer to train than the classical model.

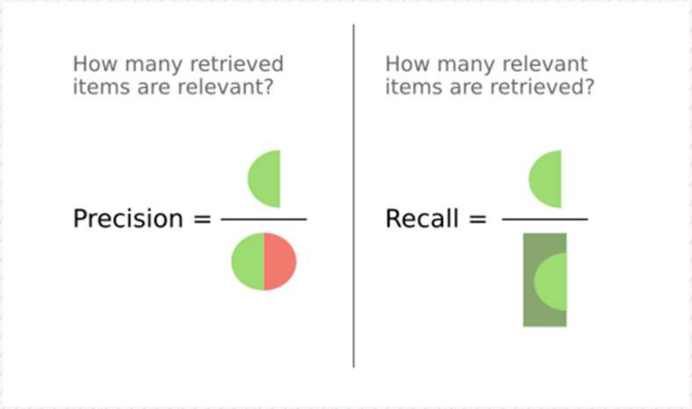
- Best SVM: C=0.1, kernel=linear, gamma=0.01
- Best VQC: ExcitationPreserving ansatz with 3 repetitions

- During cross-validation, the most complex SVM configuration took over 1.5 hours, while the most complex VQC configuration took under 41 minutes.

Results

Model	Training Time	Accuracy	Precision	Recall	F1 Score
SVM	0.012 sec.	91.26%	91.64%	98.87%	95.12%
VQC	13.16 min.	54.09%	82.47%	47.74%	60.48%




How many retrieved items are relevant?
Precision =
How many relevant items are retrieved?
Recall =

- VQC was slightly more accurate than choosing a category at random.
- VQC had better precision than recall.

Precision Vs. Recall Explanation [13]

Discussion

- The classical model performed well, correctly classifying relationship satisfaction over 90% of the time.
- The quantum model performed poorly, but its lower training time for complex configurations suggests potential efficiency advantages.
- Exploring alternative QML models may improve results on this dataset.
- Future fault-tolerant quantum computers could handle higher-dimensional problems more effectively, potentially boosting performance.

Conclusions and Future Work

- Specific factors cannot be identified as being highly associated with relationship satisfaction due to the dimensionality reduction of the dataset.

- However, since satisfaction was predicted with better-than-random accuracy, it seems evident that satisfaction is associated with some features measured in the survey (personality, relationship characteristics, romantic love measures, partner perceptions, and well-being)

Conclusions and Future Work

- This project showcases quantum computing's value in the human behavior domain.

- While the chosen algorithm and dataset were not a great match, the training-time advantage of more complicated quantum models motivates further exploration with different quantum algorithms and datasets.

- Future work could apply quantum algorithms to broader areas of human behavior and relationship science, possibly using regression or clustering instead of classification.

References

[1]: https://quantum.cloud.ibm.com/learning/en/courses/basics-of-quantum-information/single-systems/quantum-information
[2]: https://newsroom.ibm.com/2023-06-14-IBM-Quantum-Computer-Demonstrates-Next-Step-Towards-Moving-Beyond-Classical-Supercomputing
[3]: https://www.thomaswong.net/introduction-to-classical-and-quantum-computing-1e4p.pdf
[4]: https://www.thomaswong.net/introduction-to-classical-and-quantum-computing-1e4p.pdf
[5]: https://youtube.com/shorts/E0lyQbJIGkU?si=v8tGRbRzope4GXHU
[6]: https://youtube.com/shorts/dK_8FkV7vyk?si=vV2LIQGdq3-Tm2lB
[7]: https://quantum.cloud.ibm.com/docs/en/api/qiskit/1.0/circuit
[8]: https://learningds.org/ch/16/ms_train_test.html
[9]: https://www.ibm.com/think/topics/support-vector-machine
[10]: https://www.researchgate.net/publication/342906139_PROMETEO_A_CNN-based_computer-aided_diagnosis_system_for_WSI_prostate_cancer_detection/figures?lo=1 CC BY 4.0 license
[11]: https://quantum.cloud.ibm.com/learning/en/courses/quantum-machine-learning/qvc-qnn
[12]: https://arxiv.org/html/2506.06662v1
[13]: https://en.wikipedia.org/wiki/Precision_and_recall

References

- https://quantum.cloud.ibm.com/learning/en/courses/quantum-machine-learning/qvc-qnn
- https://qiskit-community.github.io/qiskit-machine-learning/tutorials/02a_training_a_quantum_model_on_a_real_dataset.html#3.-Training-a-Quantum-Machine-Learning-Model
- https://qiskit-community.github.io/qiskit-machine-learning/stubs/qiskit_machine_learning.algorithms.VQC.html
- https://arxiv.org/pdf/2502.01146
- https://quantum.cloud.ibm.com/docs/en/guides/tools-intro
- https://www.geeksforgeeks.org/machine-learning/implementing-pca-in-python-with-scikit-learn/
- https://dataverse.unc.edu/dataset.xhtml?persistentId=doi:10.15139/S3/WBVMFG

Questions?

Let's Go!™