

# Financial Wellbeing

Using quantum machine learning to identify people who are in need of financial support.

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Qiskit Hackathon: July 2022

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Coach: Desiree (IBM) and Charles (Physics)

\*Thanks to Udaya for support.

# Financial Wellbeing

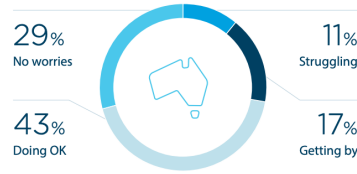
Usefulness and Complexity

## FINANCIAL WELLBEING IN AUSTRALIA AT A GLANCE

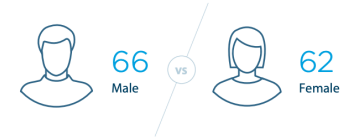
### THE FOUR COMPONENTS OF FINANCIAL WELLBEING



### FINANCIAL WELLBEING CATEGORIES IN AUSTRALIA

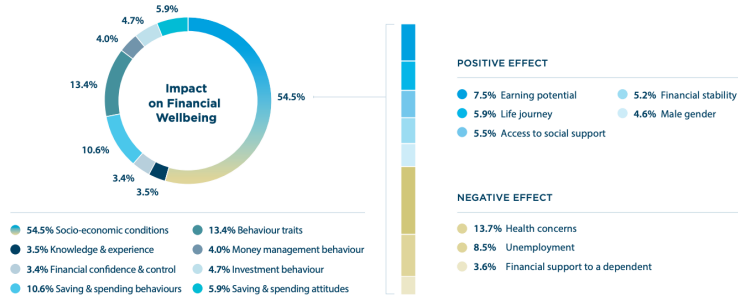


### FINANCIAL WELLBEING SCORE (OUT OF 100)



### WHAT CAN INFLUENCE FINANCIAL WELLBEING?

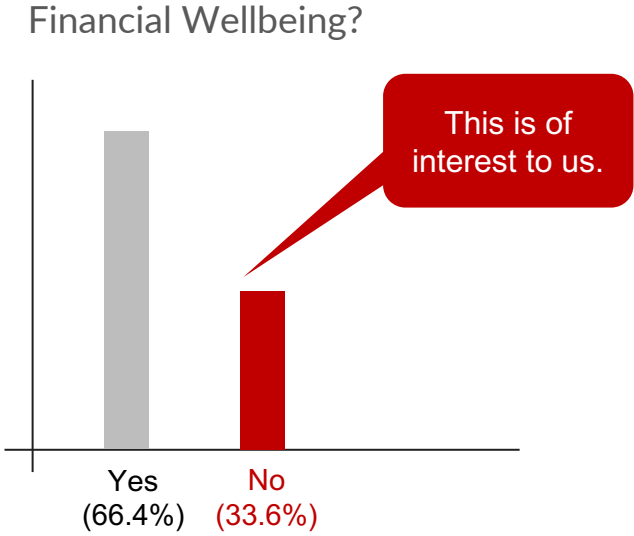
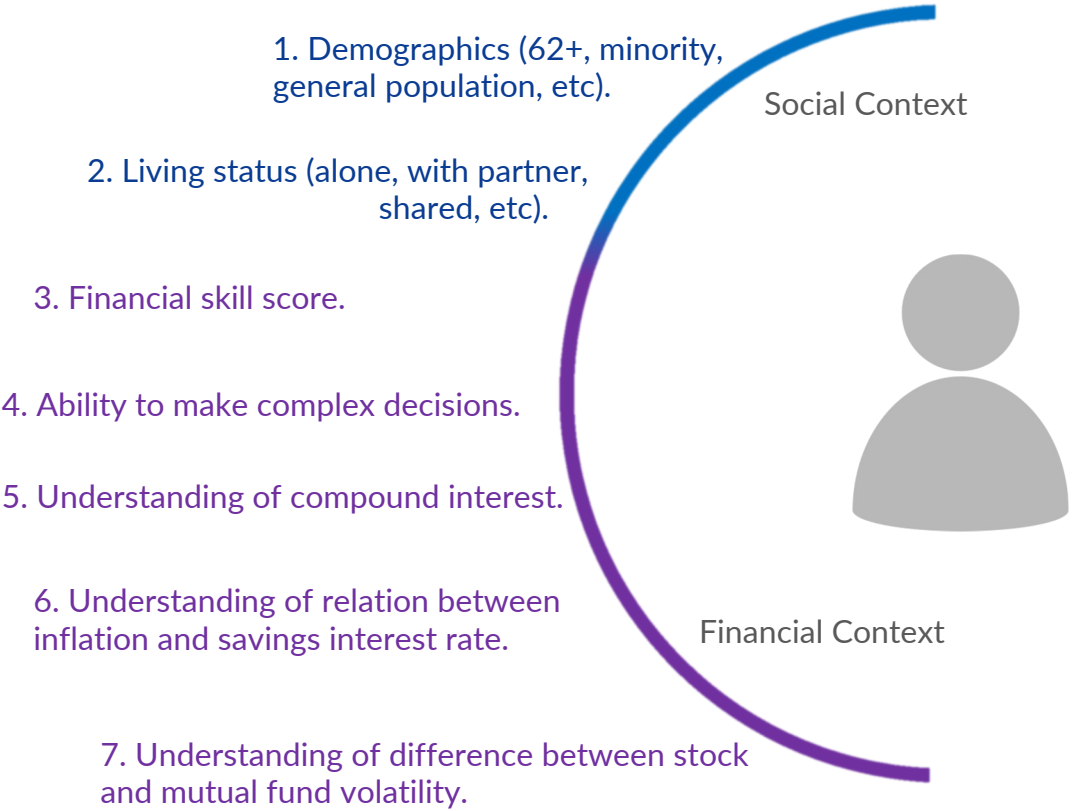
Socio-economic conditions have the largest influence on financial wellbeing



### SAVING, SPENDING AND INVESTMENT BEHAVIOURS IMPORTANT FOR FINANCIAL WELLBEING



# Classification task on real world data



Data available from consumerfinance.gov

# Results: Classical vs Quantum

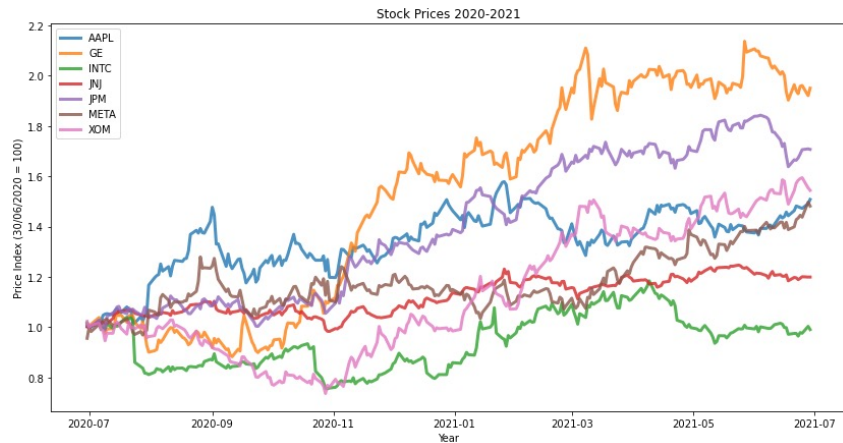
Usefulness and Complexity

	AUC	Precision	Recall	F1-Score	Time(s)
AdaBoost	0.597	0: 0.45 1: 0.73	0: 0.56 1: 0.64	0: 0.50 1: 0.68	0.006
Neural Networks (3 hidden layers)	0.67	0: 0.79 1: 0.75	0: 0.41 1: 0.94	0: 0.54 1: 0.83	0.06
Logit	0.61	0: 0.73 1: 0.71	0: 0.30 1: 0.94	0: 0.42 1: 0.81	0.016
SVM	0.64	0: 0.89 1: 0.72	0: 0.30 1: 0.98	0: 0.44 1: 0.83	0.007
Quantum VQC (ZZFeature, RealAmplitudes)	0.55	0: 0.41 1: 0.69	0: 0.48 1: 0.62	0: 0.44 1: 0.65	912.5
Quantum Kernel (ZZFeature, linear entl.)	0.55	0: 0.50 1: 0.68	0: 0.22 1: 0.88	0: 0.31 1: 0.77	954.4
Quantum Kernel (ZFeature)	0.60	0: 0.56 1: 0.71	0: 0.37 1: 0.84	0: 0.44 1: 0.77	618.2
Quantum Kernel (PauliFeature)	0.48	0: 0.25 1: 0.64	0: 0.07 1: 0.88	0: 0.11 1: 0.74	2144.75

# Portfolio optimisation on real world data

Just for fun...

Bonus?



Metrics	Expected Return	Expected Risk	Sharpe Ratio
Equally weighted	55.02%	20.94%	2.46
Classical (scipy, slsqp)	71.44%	23.02%	2.95
VQE	63.3%	21.28%	2.81
QAOA	76.34%	25.25%	2.89

Weights	AAPL	META	XOM	JNJ	JPM	INTC	GE	TSLA
Equally weighted	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12
Classical	0.00	0.25	0.00	0.05	0.30	0.24	0.16	0.00
VQE	0.10	0.30	0.00	0.10	0.10	0.20	0.10	0.10
QAOA	0.10	0.30	0.00	0.00	0.20	0.20	0.20	0.00

Note: Only one year of past daily data taken and hence Sharpe ratio is high.

# What did we learn?

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- Hackathons are fun and an *efficient* way to get into something new.
- Double (triple) check the qiskit doc. version and the installed version.
- Inputs to the VQC and Kernel methods may be different.
  - The target variable needed one-hot encoding in VQC but not in kernel methods.
- Different runs of a QML algorithm may yield diverse performance
  - Hyper parameter tuning is based on experience with these methods.
- QML methods are (currently) magnitudes slower than classical ML methods.
  - Implementing parallel processing in simulators can be tricky.
  - One needs patience (a lot of it...)
- QML methods (currently) have a lower performance than classical ML methods.
- One has to be aware of issues arising from using small datasets (in the presence of noise).

# Healthy cross-disciplinary collaboration

With advances in Quantum Computing we will be able to provide better solution methods, so that you can make better decisions.

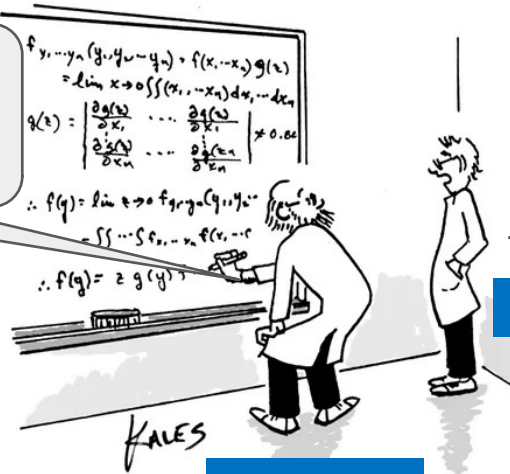
$$f(x_1, \dots, x_n, y_1, y_2, \dots, y_m) = f(x, \dots, x_n) g(y)$$
$$= \lim_{\epsilon \rightarrow 0} \int \dots \int f(x_1, \dots, x_n) dx_1 \dots dx_n$$
$$g(y) = \begin{vmatrix} \frac{\partial g(y)}{\partial y_1} & \dots & \frac{\partial g(y)}{\partial y_m} \\ \frac{\partial^2 g(y)}{\partial y_1^2} & \dots & \frac{\partial^2 g(y)}{\partial y_1 \partial y_m} \\ \vdots & \dots & \vdots \end{vmatrix} \neq 0.00$$
$$\therefore f(y) = \lim_{\epsilon \rightarrow 0} \int \dots \int f(x, y) dx$$
$$= \int \dots \int f(x, y) dx$$
$$\therefore f(y) = z g(y)$$

OK. But I don't understand how to use these methods (what is entanglement?!)

Decision Scientist

QC Expert

KALES



Thank you to UoM Physics and IBM Quantum group for organizing this event.

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