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An approach to quantum channel state estimation based on machine learning models

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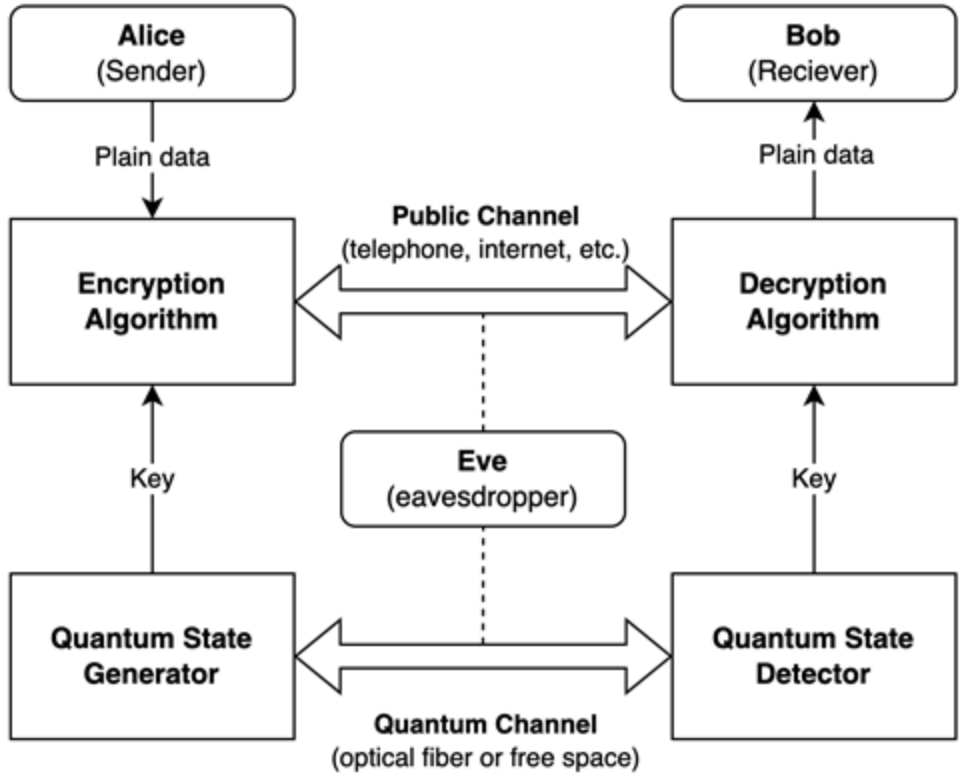
Subject area

- Devices generate the secret key, used for message encryption
- The errors in transmitted key are fixed during error correction procedure
- LDPC-based correction is faster if initial parameters are optimal
- Precise estimation of error rate (QBER) leads to more effective correction procedure



Problem definition

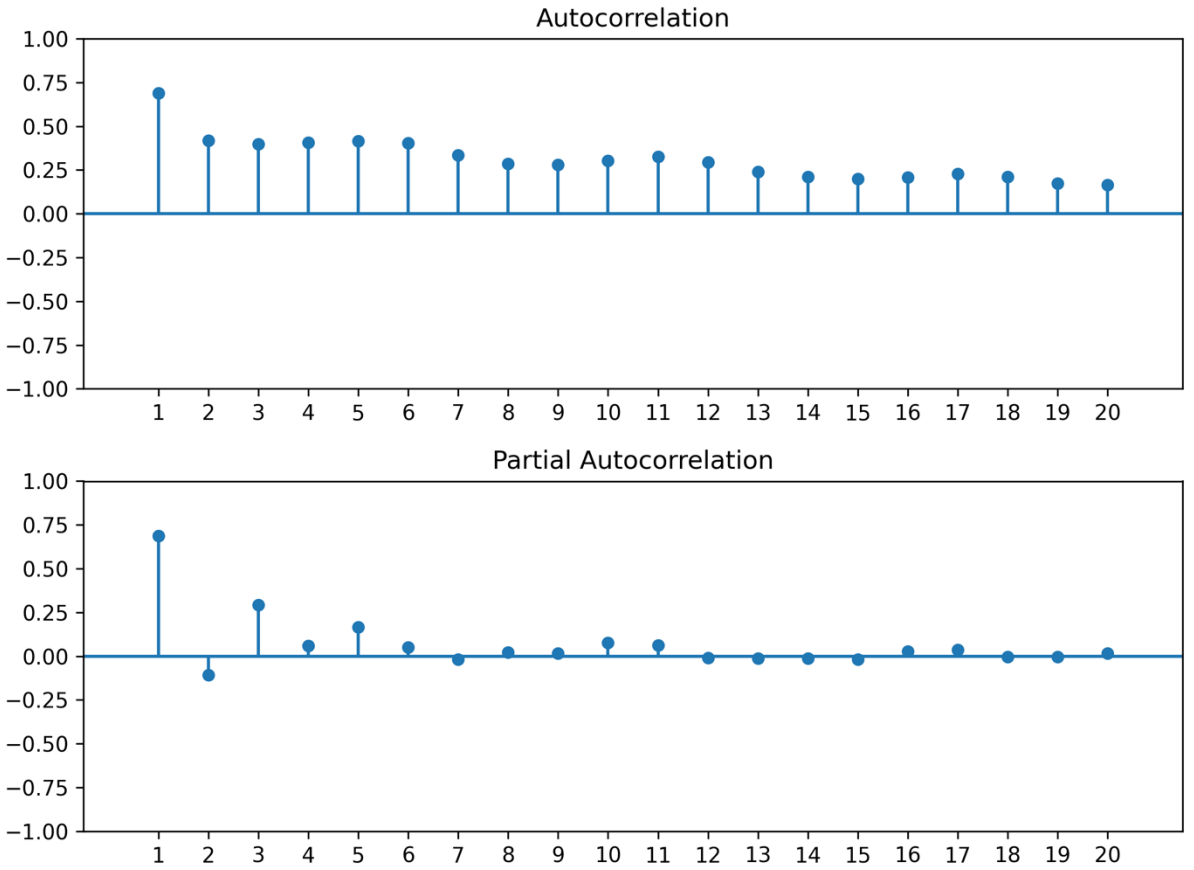
- Let $Y(t) = \{y_1, y_2 \dots y_T\}$ - multivariate time series of T points
- Let $y_t = (E_t^{\mu}, E_t^{\nu 1}, E_t^{\nu 2}, Q_t^{\mu}, Q_t^{\nu 1}, Q_t^{\nu 2})$ – different transmitter characteristics
- Let $x_t = [y_t, y_{t-1} \dots y_{t-d}]$ – previous time series points
- We want to estimate conditional expected value of the future QBER
- $E_{forecast}^{\mu} = \boldsymbol{E}\left[E_{t+1}^{\mu} \mid x_t\right]$

Problem definition

- Main metric for algorithm comparison is correction effectiveness f_{EC}
- Ratio of information actually used for reconciliation and theoretical estimation of minimum of disclosed information
- The closer to 1 – the better, usually around 1.2 - 1.3
- More precise estimation leads to better effectiveness

Existing solution

- Time series has strong autocorrelation
- Baseline utilizes exponential smoothing
- Empirically chosen $\alpha = 0.33$
- High mean squared error in non-stationary segments of time series



Machine learning approaches

- Best algorithms for time series forecasting rely on machine learning
- Statistical methods – exponential smoothing, ARIMA, regression
- Fully-connected, recurrent and transformer neural networks
- Gradient boosting on regression trees (GBRT)
- Ensembles of these algorithms

Gradient boosted exponential smoothing

- Time series specific modification with ES as first weak learner
- Does not require additional transformations
- More effective than neural networks, more precise than ES

$$\hat{y} = f_{AR}(x) + \alpha f_{GB}(x)$$

$$\sum_i \left(y_i - f_{AR}(x_i) - f_{GB}(x_i)\right)^2 \rightarrow_{GB} min$$

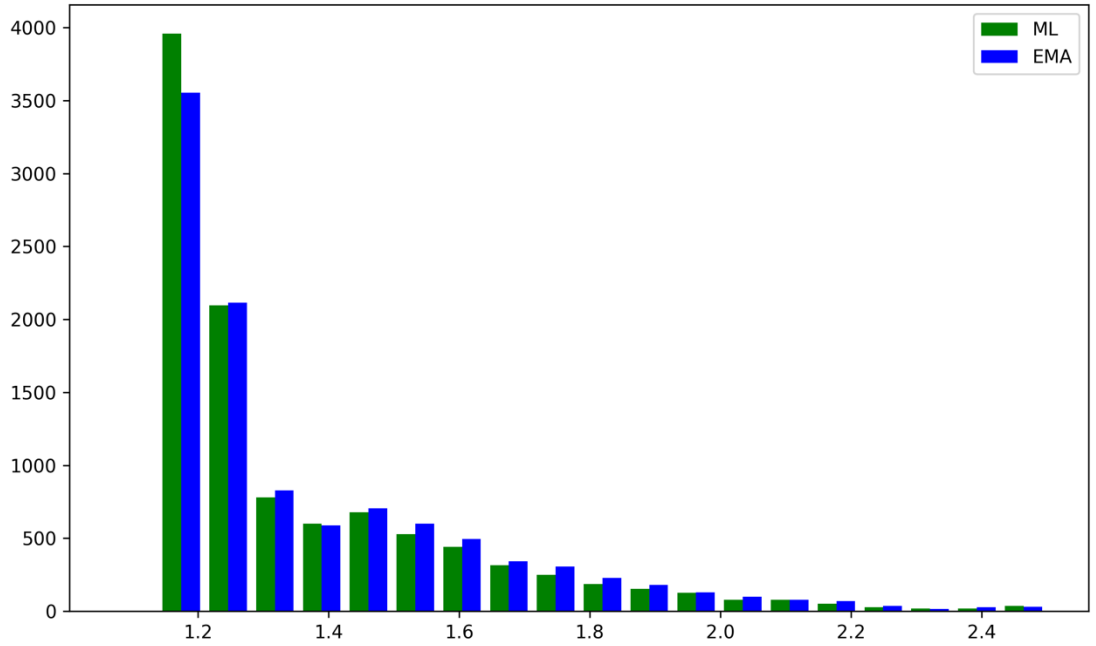
Forecasting metrics on test datasets

Model	Exponential smoothing	ARIMA	Kernel regression	Multilayer Perceptron	LSTM	Transformer	Gradient Boosting	Gradient Boosted ES
R^2	0.42868	0.55983	0.58688	0.58804	0.61842	0.38473	0.62576	**0.62838**
RMSE	0.00543	0.00477	0.00462	0.00461	0.00452	0.00520	0.00435	**0.00434**
MAE	0.00336	0.00279	0.00268	0.00267	0.00277	0.00303	0.00252	**0.00245**
MAPE	0.13154	0.10892	0.10332	0.10085	0.10817	0.11804	0.09703	**0.09463**

- Gradient Boosted ES is the best model by offline evaluation

Experiments

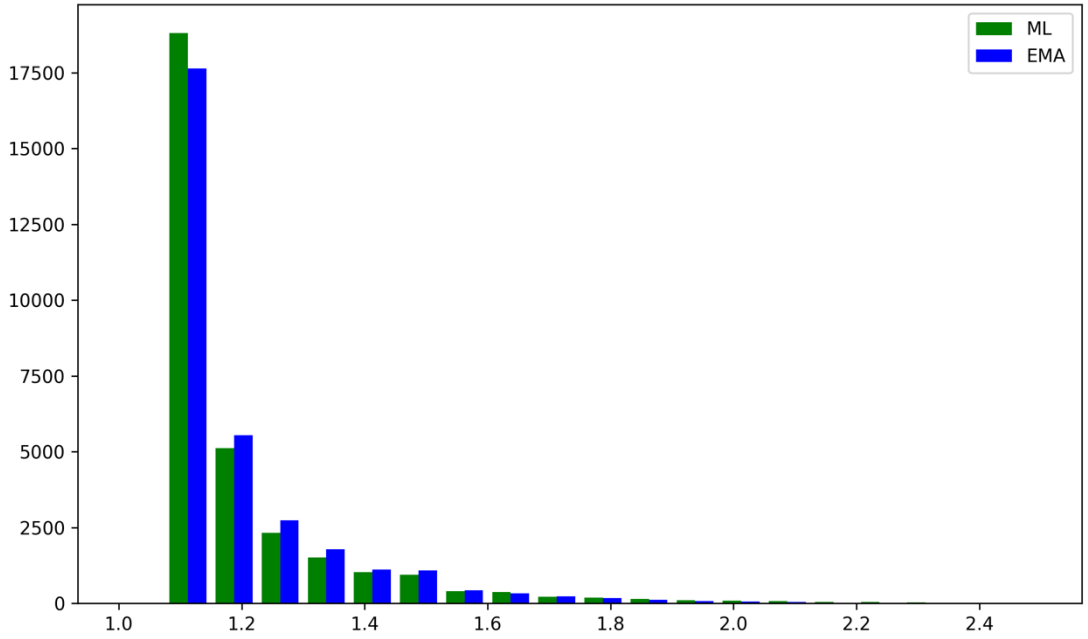
- Conducted on real transmitters using Thrift microservices
- Gradient Boosted ES as best model, trained on whole dataset
- Significant improvement of f_{EC}
- Mean equality test $pvalue \approx 10^{-6}$



$$\overline{f_{EC}^{ML}} = 1.349, \overline{f_{EC}^{EMA}} = 1.368$$

Experiments

- Not enough generalization leads to precision decrease with OOD samples
- GBRT with periodical retraining during runtime for real-time adaptation
- No significant improvement of f_{EC}
- Mean equality test $pvalue \approx 0.257$



$$\overline{f_{EC}^{ML}} = 1.229, \overline{f_{EC}^{EMA}} = 1.230$$

Conclusion

- Proposed forecasting techniques improve the quantum key correction speed in experiments on real transmitters
- In some condition model performance can decrease due to hard generalization and dominance of stable QBER time series in collected data
- The study will help advance the research of quantum cryptography and increase the quantum key generation speed in QKD systems

Thank you for attention!