Good morning, everyone. I'm Justin Tsai from the National Chi Nan University in Taiwan, and today I'm excited to share our research: "Automatic Change-Point Detection Using Piecewise Support Vector Quantile Regression."

(Move to Slide 2: Outline)

First, I'll talk about the motivation behind our work. Then, I'll introduce the framework of our proposed model. After that, I will walk you through the experiments we conducted and discuss the results. Finally, I'll conclude with our findings and suggest some directions for future work.

(Move to Slide 3: Pattern Change Detection)

So, what is pattern change detection? In many fields, such as finance, IoT, and healthcare, time-series data often contains abrupt changes in its underlying pattern. These are called "change-points." Detecting these points is crucial for understanding market dynamics and making accurate predictions. As you can see from this chart of the S&P 500 index, the trend isn't a single straight line; it's a series of different trends, indicated by the red lines. The red circles highlight where these change-points occur.

(Move to Slide 4 & 5: PCD Statistical Methods)

There are many existing methods to detect these change-points, which were categorized into five classes by Gupta et al. in 2024. These classes are statistical methods, Bayesian methods, time-frequency methods, machine learning methods, and hybrid methods. However, no single method can fit every dataset, as performance highly depends on the characteristics of the data.

(Move to Slide 6: Hybrid Methods)

Among these, hybrid methods often outperform others in accuracy and versatility because they combine the strengths of other approaches.

(Move to Slide 7 & 8: Key Challenges)

However, as also identified by Gupta et al., several key challenges remain in this field. First, detecting multiple change-points accurately is difficult. Second, handling complex, high-dimensional data or data with missing values is still a significant hurdle. They also noted the importance of providing prediction intervals, which give us a range of likely future values and offer more valuable, actionable information. This is where our work comes in.

(Move to Slide 9, 10, & 11: PSVQR Framework)

To address these challenges, we developed the PSVQR framework, which stands for Piecewise Support Vector Quantile Regression. Our approach has three core components.

First, we use Support Vector Regression, or SVR. We adopt the l1-norm for robustness and a kernel-free approach for interpretability. Second, we incorporate a Piecewise Linear Model, which is specifically designed to detect multiple change-points by fitting different linear functions to different segments of the data. And third, we use a Quantile Loss Function. This allows us to predict not only the median value but also different quantiles, which is how we generate valuable prediction intervals.

By combining these three elements, our PSVQR model has three key features: it is robust to noise and outliers, it can detect multiple change-points automatically, and it provides interval predictions.

(Move to Slide 12: The Proposed Model)

This is the mathematical formulation of our model. The first term of the objective function minimizes the l1-norm of the SVR. The second term is our quantile loss function, which allows us to set different tau values to generate prediction intervals. For a higher tau, we focus on minimizing ksi-plus, while for a lower tau, we focus on minimizing ksi-minus. The third term aims to minimize the number of change-points. The constraints are derived from SVR, but with the key difference that we've added the piecewise term. In this term, 'pt' represents a suspected change-point, while 'bt' is the coefficient for that specific pattern segment.

(Move to Slide 13: Experiment Design)

Now, let's look at our experiments. We used S&P 500 daily price data from July 2024 to July 2025. First, the VIX and price data need to be standardized using a z-score. We then tested two versions of our model: PSVQR-1f, which uses only a sequential index as a feature, and PSVQR-2f, which uses both the index and the VIX, or Volatility Index. We compared their performance against the well-known ARIMA model as a benchmark, using a one-step ahead forecasting approach, and measured performance using MAPE, RMSE, and NSE metrics.

(Move to Slide 14 & 15: Prediction Results - Index only)

First, looking at the model with just one feature, PSVQR-1f. The results show that its performance is competitive, particularly at the 0.9 quantile, where it achieves a high NSE score. The graph on the next slide shows that it does a good job of identifying the major change-points in the training data, marked by the green lines, and the model can dynamically detect these change-points.

(Move to Slide 16 & 17: Prediction Results - Index and VIX)

Next, we added the VIX as a second feature. The results for PSVQR-2f show a significant improvement across all quantiles. The MAPE and RMSE values are lower, and the NSE scores are consistently higher, indicating much better predictive accuracy. As you can see in the graph, this model can also dynamically detect the change-points.

(Move to Slide 18: Comparison of PSVQR-f1 and PSVQR-f2)

Comparing the two side-by-side, it's clear that including the VIX helps the model capture the data's behavior more accurately for prediction. However, the simpler model, PSVQR-f1, appears to identify the larger, more structural breaks more cleanly, suggesting it may be better suited for pure change-point detection tasks.

(Move to Slide 19: Compare to Benchmark)

Here, we compare our PSVQR-2f model directly with the ARIMA benchmark. The blue line is ARIMA, and the red line is our model. You can see that our model's predictions track the actual price much more closely, especially during periods of high volatility, such as the one during the reciprocal tariff event. This demonstrates the robustness and superior predictive power of our approach.

(Move to Slide 20: Conclusion)

In conclusion, our experiments show that the PSVQR model, particularly the version with two features, outperforms the traditional ARIMA model in stock price prediction. Our method also predicts the value of change-points more precisely. Interestingly, we found a trade-off: the single-feature model seems better for a clean detection of major change-points, while the two-feature model is superior for prediction tasks.

(Move to Slide 21: Future Work)

Looking ahead, there are several directions for future work. We plan to find a proper method to determine the penalty for the number of change-points. We also want to incorporate more features and compare our model against a wider range of other change-point detection methods. Finally, we aim to improve computational efficiency by moving from a CPU-based solver to GPU solutions, such as the new version of Gurobi or NVIDIA's cuOpt.

(Move to Slide 22: Thanks!)

That is all of my presentation. Thank you, and I’d be happy to answer any questions you may have. If you'd like to get in touch, please feel free to email me.