🎤 口語版簡報稿

Good morning, everyone!
My name is Sheng-Yu Tsai from National Chi Nan University, but you can just call me Justin.

Today, I'd like to share our research called "Automatic Change-Point Detection Using Piecewise Support Vector Quantile Regression," or simply PSVQR.

It's a hybrid model that can automatically detect change points and also give confidence intervals using quantile loss.

Slide 1 – Motivation

Before we get into the model itself, let me talk a bit about our motivation.

Pattern Change Detection, or PCD, in time-series data is really important.
It helps us find structural changes in areas like finance, healthcare, IoT, and manufacturing.

Here's an example — the S&P 500 index from July 18, 2024 to July 22, 2025.
(click)
As you can see, there are several different patterns in this period, shown by the red line segments.

To capture those patterns, we first need to find the change points — (click) the red circles on the graph.

There are already some existing methods for this task, and we'll take a quick look at them next.

Slide 2 – Existing Methods

According to a paper called "Comprehensive Analysis of Change-Point Dynamics Detection in Time Series Data" by Gupta et al.,
change-point detection methods can be divided into three main categories:
parametric, non-parametric, and hybrid approaches. (click)

But the truth is — there's no single method that works perfectly for every dataset.
It really depends on what kind of data you have.

Slide 3 – Why a Hybrid Method?

That's why hybrid methods are often preferred.
They combine the strengths of both parametric and non-parametric models,
so they're usually more flexible and more accurate when dealing with complex changes.

And that's exactly why we wanted to develop our own hybrid model — the PSVQR.

Slide 4 – Challenges

In the same paper, Gupta et al. also pointed out some major challenges in PCD:

- **Detecting multiple change points,**
- **Handling high-dimensional or missing data,**
- **And processing large datasets efficiently.**

They also mentioned that uncertainty estimation is quite difficult, especially for non-parametric models.

So in our research, we mainly focus on two of these challenges —
detecting multiple change points and estimating uncertainty.

Slide 5 – Our Proposal

To tackle these challenges, we propose a hybrid optimization approach for automatic change-point detection and interval forecasting,
called the Piecewise Support Vector Quantile Regression, or PSVQR. (click)

Slide 6 – Model Components

The PSVQR model has three main parts:

1. **A Quantile Loss Function, which helps us build confidence intervals.**
2. **A Support Vector Regression using L1-norm to make it more robust to outliers.**
3. **And a Piecewise Linear Model, which can adapt to different segments or patterns in the data.**

Slide 7 – Optimization Framework

These three parts are combined using multi-objective optimization.
That's how the model can balance accuracy, robustness, and interpretability.

Slide 8 – Key Features

So overall, the PSVQR model has four main features:

- **Interval prediction,**
- **Robustness to noise and outliers,**
- **Multiple change-point detection, and**
- **Feature selection.**

Slide 9 – Model Form

This slide shows the general form of our model.
But to make it easier to explain, I simplified it here to a single-feature version.

Slide 10 – Objective and Constraints

In our objective function, we minimize three things:

1. **The L1-norm from the SVR,**
2. **The quantile and epsilon-insensitive loss, and**
3. **The number of change points.**

And for the constraints, a point P_t is recognized as a change point only if b_t exists and its value is smaller than ξ.

Slide 11 – Experiment Design

For the experiment, we used the S&P 500 dataset.
We standardized both the features and the price data, then ran the PSVQR model and compared it with ARIMA.

The prediction was done one step ahead,
and we evaluated the results using MAPE, RMSE, and NSE.

Slide 12 – Results

Here are the results. (pause to show figure)
We can see that the PSVQR model captures the key turning points quite well.

Slide 13 – Conclusion

In summary, the PSVQR model performs better than ARIMA in all evaluation metrics.
It also does a great job handling spiky points in the data.

We also found that the performance is highly affected by the penalty parameter, rho (ρ) —
If rho is too small, the model might overfit;
if it's too large, the model might lose accuracy.

Slide 14 – Future Work

For future work, we plan to:

- **Find a better way to set the penalty parameter rho,**
- **Move our solver from CPU to GPU to make it faster,**
- **And compare PSVQR with more change-point detection and forecasting models using different datasets.**

Closing

That's all for my presentation.
Thank you so much for listening —
and I'll be happy to answer any questions you might have!

Introduction

Parametric statistical methods have limitations, including reliance on strict distributional assumptions, which can lead to inaccuracies when these assumptions are unmet. They are often unsuitable for real-time use and struggle to detect complex shifts, such as changes in frequency or auto-correlation. Identifying multiple change-points in multimodal data also remains a challenge. However, non-parametric statistical methods also have several limitations, such as requiring more data to achieve the same precision as parametric methods, being computationally expensive with large datasets, and being prone to overfitting noise due to their high adaptability. Additionally, quantifying uncertainty, such as confidence intervals, can be more challenging in non-parametric settings. Even in hybrid methods, each change-point needs to be examined iteratively (Gupta et al., 2024). Thus, it inspires us to develop a hybrid method to provide prediction interval and detect the change-points simultaneously rather than iteratively.

重點：

Properly managing PCD prevents missed intervention opportunities, false alarms, and misinterpretations.

主要問題：

Gupta et al. (2024) concluded that key challenges in PCD include detecting multiple change-points, handling high-dimensional or missing data, and processing large datasets efficiently. Future work should focus on improving computational efficiency, integrating PCD with concept drift, and developing hybrid methods to enhance accuracy and reduce false detections. They also noted that quantifying uncertainty, such as confidence intervals, is more challenging in non-parametric settings than in parametric ones.