Polished Presentation Script

Good morning, everyone.
My name is **Sheng-Yu Tsai** from **National Chi Nan University**, but you can also call me **Justin**.
Today, I'm going to present our research titled **"Automatic Change-Point Detection Using Piecewise Support Vector Quantile Regression,"** or simply the **PSVQR model**.

This model is a **hybrid approach** that can automatically detect change points in time-series data and also provide **confidence intervals** through **quantile loss**.

Slide 1 – Motivation

Before introducing the PSVQR model, I'd like to start with our **motivation**.

Pattern Change Detection (PCD) in time-series data is essential for identifying structural shifts in many fields — such as **finance, healthcare, IoT, and manufacturing**.

For example, here we can see the **S&P 500 index** from **July 18, 2024 to July 22, 2025.** (click)
This graph contains several different patterns, shown as the **segments of the red line**.

To capture those patterns, we first need to **detect the change points** — (click) which are shown here as **the red circles**.

There are several existing methods for solving this problem, and we'll look into them next.

Slide 2 – Existing Methods

According to the paper **"Comprehensive Analysis of Change-Point Dynamics Detection in Time Series Data"** by **Gupta et al.**,
the existing **PCD methods** can generally be categorized into **three classes**:
Parametric approaches, Non-parametric approaches, and Hybrid approaches.
(click)

However, **no single approach** is universally effective for detecting pattern changes. The performance of each method highly depends on the **characteristics of the dataset**.

Slide 3 – Why a Hybrid Method?

Among these, **hybrid methods** often outperform others because they combine **accuracy** and **versatility**,
allowing for the efficient detection of **complex pattern changes** across different types of data.

That's one of the key reasons why we propose our **PSVQR model**, which is also a **hybrid approach**.

Slide 4 – Challenges in PCD

Gupta et al. also summarized several **key challenges** in pattern change detection, including:

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

They also noted that **uncertainty estimation** is particularly difficult in **non-parametric models**.

In our research, we mainly focus on **detecting multiple change-points** and **quantifying uncertainty**.

Slide 5 – Proposed Method

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

Slide 6 – PSVQR Components

The **PSVQR framework** consists of **three main components**:

1. **Quantile Loss Function** – provides **confidence intervals** using different quantile levels.
2. **Support Vector Regression (SVR)** – we use an **L1-norm** instead of L2 to make the model more **robust to outliers**.
3. **Piecewise Linear Model** – allows the model to **fit different segments** of the time series flexibly.

Slide 7 – Optimization Framework

These three components are integrated through a **multi-objective optimization** framework.

Slide 8 – Model Features

As a result, the **PSVQR model** has **four key features**:

- **Interval prediction**,
- **Robustness to noise or outliers**,, and
- **Multiple change-point detection**,

Slide 9 – Model Formulation

This slide shows the **general form** of our model.
For simplicity, I'll explain it using the **single-feature version** shown here.

Slide 10 – Objective and Constraints

In our **objective function**, we aim to minimize three main terms:

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

In the **constraint functions**, a time point P_t is considered a **change point** only if b_t has a value and that value is smaller than ξ.

Slide 11 – Experiment Design

For our experiment, we used the **S&P 500 dataset**.
All input features and prices were **standardized** before applying the model.

We compared **PSVQR** with the **ARIMA model** using **one-step-ahead prediction**.
The evaluation metrics include **MAPE, RMSE, and NSE**.

Slide 12 – Results

Here are our **experimental results**.
(Explain figure briefly when presenting)

Slide 13 – Conclusion

In summary, our **PSVQR model** outperforms the **ARIMA model** in all performance metrics.
It also performs especially well on **spiky or volatile points**.

We also found that the model is **sensitive to the penalty parameter** of ρ:

- A **smaller penalty** may lead to **overfitting**,
- While a **larger penalty** reduces accuracy.

Slide 14 – Future Work

For future work, we plan to:

- Develop a more effective method to **set the penalty parameter** ρ,
- **Transfer** our current **CPU-based solver** to a **GPU-based solution**, and
- **Compare** PSVQR with more **change-point detection and prediction models** across **various datasets**.

Closing

Thank you very much for your attention.
I'll be happy to answer any questions.

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.