Generative Adversarial Network (GAN) model in Asset Pricing

Planning: 164 words / minute, total 20 minutes (1200 sec) presentation → max 3280 words.

Summary of time taken:

1. Motivation (90 sec)
2. Literature review (100 sec)
3. Research objective (54 sec)
4. Methodology (155 sec)
5. Evaluation metrics (30 sec)
6. Data (83 sec)
7. Results (500 sec)
8. Discussion (40 sec)
9. Conclusion (58 sec)

Slide 1: title slide (25 sec)

Good afternoon professors, my name is Lingjie and welcome to my thesis presentation.

I will be presenting on Generative Adversarial Network model in Asset pricing. I will use the term "GAN model" to describe the model from now on.

If you have any questions, please feel free to ask me at the end of the presentation.

Slide 2: overview (25 sec)

I will first explain the motivation that drives this paper, and the current development in the literature before introducing my research objective.

Thereafter, I will explain the methodology, evaluation metrics, and data before showcasing the results.

Finally, I will end the presentation with some discussion and conclusion.

Slide 3: motivation (50 sec)

Our paper falls in the domain of asset pricing. One important goal in asset pricing is to explain the variation in asset returns.

No-arbitrage pricing theory explains the asset returns with a pricing kernel, also known as stochastic discount factor. We use the term "SDF" in this presentation.

However, a question remains: what exactly is this SDF, and how do we estimate it?

There are three challenges in estimating the SDF. Firstly, choosing the right factors, or data features, for estimation.

Secondly, selecting the right combination of assets, or portfolio, for estimation.

Lastly, estimating the functional form of the SDF.

Let's first take a look at how the current literature answers these challenges.

Slide 4: literature review (50 sec)

The first few models used in asset pricing were proposed in the 60s and 90s and are still regarded as the benchmark model today.

These models include Capital Asset Pricing Model, Fama and French three factor and Carhart four factor model. These models estimate the SDF with an OLS and some constructed factors.

Following the literature, the factors in these classical models will be address as "extended Fama French factors".

Literature after the 90s expanded the search for more factors. Feng used the term "factor zoo" to describe the hundreds of new factors proposed in the literature.

However, the search for factors does not end here. Freyberger and Feng reviewed all proposed factors and found few of them are relevant in explaining the asset returns.

Slide 5: literature review (cont) (55 sec)

Beyond the factor search, literature also explored non-linear, and non-parametric SDF estimation.

Gu compared various machine learning models and found neural network model as the best performing one. However, the improvement in neural network compare to fama french model is only marginal.

The latest research therefore expanded on the classical machine learning to introduce economic theory in model estimation.

Chen proposed the GAN model used in this paper and Gu proposed an Autoencoder neural network. Both models improve upon standard neural network with no-arbitrage pricing theory.

Chen also found that including macroeconomic data further improves the SDF estimation.

Summarizing the current literature, SDF seems to be a general function of potentially infinite factors, while including macroeconomic data and imposing economic theory can further improve the empirical SDF estimation.

Next, let me formally introduce our research objective.

Slide 6: research objective (54 sec)

Our research is built on Chen's work. We aim to examine the GAN model's external validity with United Kingdom London Stock Exchange data.

Our paper contributes to the limited literature done on non-US market.

Most literature focus only on the US data, resulting in a "home bias". Our research aims to investigate if the best performing model in the US will continue to perform in other regions.

There are four key findings in our research: Firstly, the GAN model outperformed the benchmark four-factor model even in the UK market. Secondly, macroeconomic data is important in the SDF estimation. Thirdly, extended fama french factors are the most important covariates in the SDF estimation and Lastly, these factors are nearly linear in the SDF. However, there are interaction effects between the factors.

We will now explain the methodology in depth to arrive at these results.

Slide 7: methodology: no-arbitrage pricing model (52 sec)

The first model we will be introducing is the no-arbitrage pricing model, which motivates our loss function.

The model assumes an asset independent, time-dependent SDF such that there is no excess return in expectation. Equation 1 shows this relationship formally.

We can also express the SDF as an affine transformation of a tangency portfolio F. The tangency portfolio is any portfolio that maximizes the mean-variance efficiency, and is constructed as a weighted portfolio of all possible assets. We assume this SDF weight omega is a function of firm characteristics data I ti and macroeconomic data I t

We consider one specific tangency portfolio where a = 1, b = 1, then the no-arbitrage asset pricing model can be expressed as a function of the SDF weight shown in equation 2

Slide 8: methodology - no-arbitrage pricing loss (30 sec)

However, if no-arbitrage pricing model alone is insufficient to explain the variations in asset returns, then we can define a competing function g such that there is no excess return in expectation only when we consider both the no-arbitrage pricing model and the conditional moment function g as shown in equation 3

This g function can be viewed as selecting portfolio and factors that no-arbitrage pricing model is least able to explain.

Equation 3 motives our pricing loss function used in the GAN model estimation. The loss function is shown in equation 4.

Slide 10: methodology - neural network model (37 sec)

The backbone of the GAN model is various kinds of neural network model.

We will first explain a simple feed-forward neural network model before explaining the GAN model.

A feed-forward network consist of one input layer one or more hidden layers and one output layer.

In essence, feed-forward neural network performs a linear combination of covariates before passing the intermedia output to a non-linear function h

The output from the non-linear function is then linearly combined again, and the procedure repeats until the output layer, producing the final output

Besides the feed-forward neural network, our GAN model also uses a recurrent neural network LSTM which takes into consideration the time dynamic nature of macroeconomic data.

Slide 11: methodology - GAN model (35 sec)

To construct the GAN model, we use two competing neural network models.

The first model, called the discriminator, estimates the SDF weight omega while the second model, called the generator, estimates the conditional moment function g.

The GAN training procedure can be viewed as a zero-sum game where the discriminator minimizes the pricing loss while generator maximize the pricing loss.

The objective here is to achieve a Nash-Equilibrium where the discriminator best approximates the SDF function while generator is able to construct portfolio and factors that no-arbitrage pricing theory is least able to explain.

Next, we will take a look at how to train the GAN model

Slide 12: methodology - GAN model structure (15 sec)

As shown in Figure 2, the GAN model training involves the discriminator and generator linked by a single pricing loss function.

Both models take the firm characteristics data and macroeconomic data as input, but produce different outputs.

As mentioned earlier, the objective here is to sequentially train the discriminator and generator through a min max optimisation in order to achieve a Nash equilibrium

Slide 13: methodology - benchmark four-factor model (16 sec)

The benchmark model used in this paper is the Carhart four-factor model.

The four extended fama french factors in this model are market risk, difference in returns between big and small firms, difference in returns between high value and low value firms, and the momentum factor.

The factor model is estimated through standard OLS regression.

Slide 14: evaluation metrics - Sharpe Ratio (30 sec)

We use Sharpe ratio as the evaluation metric

Sharpe ratio was proposed by Sharpe to evaluate the performance of risk-adjusted assets relative to a risk-free asset.

The formulation of Sharpe ratio express the desire to maximize excess return while minimizing risk. The risk is approximated by the standard deviation of asset returns.

A higher Sharpe ratio indicates a better performing portfolio and tangency portfolio by definition achieve the highest Sharpe ratio possible.

Slide 15: Data - UK LSE (40 sec)

The data used in this paper consist of UK LSE monthly stock prices from 1998 to 2017.

The stock prices are extracted from Yahoo! Finance and we compute the log difference as the stock returns.

The risk-free rate and fama french factors were provided by Gregory, while the firm characteristics data is retrieved from paid data subscription service Finage.

The UK macroeconomic data is provided by Coulombe.

In total, our data contains 132 covariates, 942 stocks with maximum of 20 years returns.

Slide 16: Data - Data splitting (43 sec)

We divide the data into three periods, 12 years of training data, 4 years of validation data and 4 years of out-of-sample test data.

We constructed two different data splits to maximise the available data. The first split is called “Factor data” as it contains only extended fama french factors and macroeconomic data. This dataset contains 942 stocks with 116 covariates.

The second data split is called “Fundamental data”, which consist of firm income statement data on top of the covariates available in the “Factor data”.

The two data split is essential as we only keep the stocks with full covariates in a particular month, and Finage database only contains limited income statement data for a subset of stocks.

Slide 17: Results - Sharpe ratio

Now, let us analyze the empirical results.

First we compare the out-of-sample Sharpe ratio between GAN models and benchmark factor model. We found that GAN models generally achieve a higher Sharpe ratio than the four-factor model.

We notice that the GAN model trained with only factor data performed worse than the factor model. Our hypothesis here is the limited covariates in this GAN model affect the neural network estimation.

Next, we compare the out-of-sample Sharpe ratio between GAN models trained with macroeconomic data to those without.

We notice that GAN models trained with the macroeconomic data achieve a higher Sharpe ratio than those without. Suggesting that including macroeconomic data is important in SDF estimation.

Furthermore, the best performing GAN model is trained on factor data with macroeconomic data.

Sharpe ratio provide a summary statistics to compare the models, but why are GAN models better performing, and what are the key covariates required for SDF estimation?

These are the questions we will be exploring next

Slide 18: Results - Variable Importance

To better understand how each variable affects the SDF weight, we computed a sensitivity score The sensitivity score measures the average absolute gradient of the SDF weight, as a function of the individual covariates.

Figure 3 shows the individual variable importance. We normalise the sum to be 1 and a higher score indicates a more important variable.

The most important variable belong to the extended Fama French factors, followed by firm specific past return data and macroeconomic indexes affecting consumers, business and general stock market.

One interesting observation is that the UK SDF weight function is also affected by the US S&P 500. This suggests that we could potentially improve the UK SDF estimation with the US market data.

Slide 19: Results - SDF structure

We analyse the SDF weight structure to better understand why the GAN model is able to outperform the four-factor model.

We plot the SDF weight structure as a function of the individual factors. With reference to the first image in Figure 4, the x-axis is the value of the high minus low while the y-axis is the SDF weight. All other factors were kept at their mean values in this image.

As shown in the first image, there is a near linear relationship between high minus low and the SDF weight. This might be the reason why linear factor model is able to perform well.

We can investigate the interaction effect between factors by varying the value of other factors. The different colored lines in the second image indicate different values of market risk. We notice that as we vary the market risk, the impact of high minus low on the SDF weight changes. Image three and four shows similar observations when we change small minus big and momentum values.

This observation suggests that there is an interaction effect between the factors. Therefore, models that are able to take into consideration these interaction effects, such as neural network model, will outperform the factor model.

Lastly, the observation here also holds when we look at factor other than high minus low and is consistent with the result in Chen's US SDF estimation.

Slide 20: Discussion - Limitation (40 sec)

No paper is perfect, so is ours.

One key limitation of this paper is the considerable gap between Chen's dataset and our dataset.

Chen's data includes 50 years of historical data with over 10,000 stocks while our paper contains 20 years of data with 942 stocks.

The data-poor nature of the UK market could be one of the crucial reason why most literature focus on the US data. Even the paid subscription provider was not able to furnish complete and rich data comparable to the US.

Nonetheless, the results in this paper are still relevant in assessing the performance of the GAN model when subject to data limitations.

Slide 21: Conclusion (50 sec)

In conclusion, our paper set to examine the external validity of Chen's GAN model using the UK LSE 1998 - 2017 data, and we deliver four key findings.

Firstly, we found the GAN model indeed outperformed benchmark four-factor model in terms of Sharpe ratio.

Secondly, similar to Chen's finding, including macroeconomic data improves the SDF estimation.

Thirdly, the extended fama french factors are the most important covariates in SDF estimation, and they are nearly linear in the SDF, explaining the wide popularity of fama french model.

Lastly, there are interaction effects between factors and models that is able to take into consideration these interaction effects will outperform the fama french factor model.

Slide 22: Thank you and questions (8 sec)

With that we have come to the of our presentation. Thank you, and please feel free to ask any questions.