Examples of Machine Learning Applications in Economics

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Presentation Outline

Goal

- Today, we will go over a few examples of how machine learning is used in economics.
- We will focus on three areas:
  - Dimension reduction (Gürkaynak, Sack, and Swanson (2005))
  - Pre-processing data (Handlan, Moschini, and Sheng)
  - Structural estimation (Kaji, Manresa, and Pouliot (2022))

Presentation Outline

1. Introduction
2. Gürkaynak, Sack, and Swanson
3. Handlan, Moschini, and Sheng
4. Kaji, Manresa, and Pouliot

Introduction

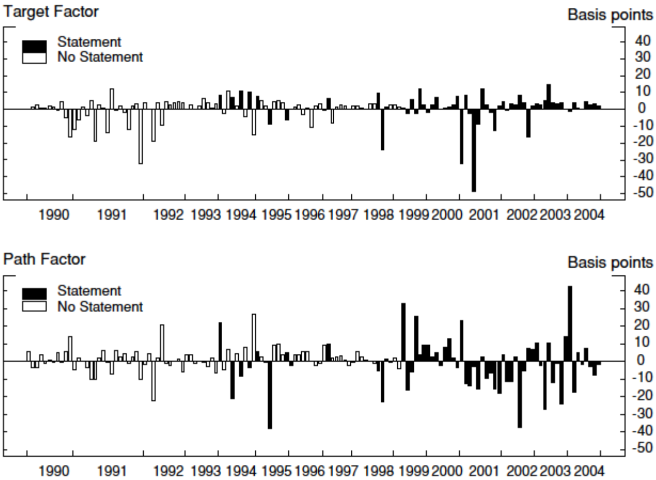
- Treasury market in Jan 2004 jumped even if current period fed funds rate remains unchanged.
- What changed was the Fed's phrasing of how long they will keep the current policy accommodation.
- **Question:** Are the effects of monetary policy announcements on asset prices adequately characterized by a single factor, namely the surprise component of the change in the current federal funds rate target?

Approach

- Used Principal Component Analysis to compute two factors of asset prices (Fed funds rate futures and Eurodollar futures)
- Under suitable rotations, these two factors can be interpreted as:
  - current federal funds rate target
  - future path of policy

The Two Factors

Figure 6. Monetary Policy Surprises as Two Factors



Results

Table 5. Response of Asset Prices to Target and Path Factors

	One Factor			Two Factors			
	Constant (std. err.)	*Target Factor (std. err.)*	R^2	*Constant (std. err.)*	*Target Factor (std. err.)*	*Path Factor (std. err.)*	R^2
MP Surprise	–0.021*** (0.003)	1.000*** (0.047)	.91	–0.021*** (0.003)	1.000*** (0.048)	0.001 (0.026)	.91
One-Year-Ahead Eurodollar Future	–0.018*** (0.006)	0.555*** (0.076)	.36	–0.017*** (0.001)	0.551*** (0.017)	0.551*** (0.014)	.98
S&P 500	–0.008 (0.041)	–4.283*** (1.083)	.37	–0.008 (0.040)	–4.283*** (1.144)	–0.966 (0.594)	.40
Two-Year Note	–0.011** (0.005)	0.485*** (0.080)	.41	–0.011*** (0.002)	0.482*** (0.032)	0.411*** (0.023)	.94
Five-Year Note	–0.006 (0.005)	0.279*** (0.078)	.19	–0.006** (0.002)	0.276*** (0.044)	0.369*** (0.035)	.80
Ten-Year Note	–0.004 (0.004)	0.130** (0.059)	.08	–0.004* (0.002)	0.128*** (0.039)	0.283*** (0.025)	.74
Five-Year Forward Rate Five Years Ahead	0.001 (0.003)	–0.098** (0.049)	.06	0.001 (0.003)	–0.099** (0.047)	0.157*** (0.028)	.34

Note: Sample is all monetary policy announcements from July 1991–December 2004 (January 1990–December 2004 for S&P 500). Target factor and path factor are defined in the main text. Heteroskedasticity-consistent standard errors reported in parentheses. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent, respectively. See text for details.

Presentation Outline

Motivation

- Quantify and analyze the differences between women's and men's experiences in the profession
- Economics seminars and conferences have been presented virtually
- **What we do:** develop a scalable and consistent method for analyzing tones and emotions to analyze people's experiences in economic seminars
- **Methodology:** convolutional neural network to classify emotions

Training Sets

- Ryson Audio-Visual Database of Emotional Speech and Song (RAVDESS)
- Toronto Emotional Speech Set (TESS)
- Crowd-sourced Emotional Multimodal Actors Dataset (CREMA-D)

Data Overview

	RAVDESS	TESS	CREMA-D	Total
# of Observations[†]	1057	2400	7442	10899
Male/Female Speaker Split	12/12	0/2	48/43	60/57
Obs Length	Sentence	Word [‡]	Sentence	Mixed
Obs Containing Age	0	2400	7442	9842

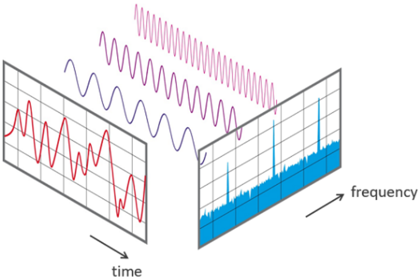
Table: Data Summary

[†] We only count the clip if its emotion label is in the set of emotions we want to look at, which are sad, angry, neutral, happy, disgust, and fearful.

[‡] These are uttered in the format of "say the word { }," so the observations across all three training sets are similar in length (2-4s).

Processing Audio Data

- **Goal**: convert raw audio into numerical representation for analysis
- **Challenge**: What features of audio data is informative and measurable?
- **Standard Approach**:
  1. We can Fourier transform audio signals from its raw waveform to a representation using **frequency** and **amplitude**, which is called the **spectrum**.
  2. To capture the dynamic properties of sound, we often compute spectra over time, producing a **spectrogram**.



What we do

Following Gorodnichenko, Pham and Talavera (2021), we extract these features that capture how sound is perceived by human ears:

- Mel-scaled spectrogram and Mel-frequency cepstral coefficients: perceptual scale of equal distance in frequencies
- Chromagram: pitch classes

These are all variations of spectrogram with different frequency scales.

More on features

What we do (cont'd)

Specifically:

- We use 12 chromas (pitch classes), 40 MFCCs, and 128 mel-scale frequencies, which gives us a feature matrix of dimension [180, number of time windows] for each audio observation.
- We take the mean over the time dimension and get a 1-d array of 180 elements as our feature set.

Network Choice

Convolutional Neural Networks (CNNs):

- Convolves inputs with learnable kernels.
  - On a high level, similar to a nonparametric regression to a categorical output variable
- Great for local feature extraction and edge detection, which is to find discontinuities or jumps in the data.
  - In an image, that means looking at changes in colors and patterns.
  - In audio, this would be a jump in elements of the spectrogram, which represents change in audio characteristics such as pitch and intensity.

Training Results

	Emotion	Seniority	Sex
Both[§]	NA%	NA%	97.61%
Male	47.53%	90.77%	NA
Female	72.07%	92.81%	NA

[§] Neural nets that are trained on data from both sexes

Presentation Outline

Motivation

- There are two common ways of estimating structural relationships:
  - Maximum Likelihood Estimation: likelihood function might not have closed form or too complex
  - Simulated Method of Moments: estimating a large number of moments have poor finite sample properties
- **Proposed Solution:** Adversarial estimation

The Basic Idea

- Inspired by generative adversarial networks
- Generator:
  - Structural model that generates fake data
  - Wants to minimize classification accuracy
- Discriminator
  - Usually a neural network
  - Wants to tell real data from generated data
  - Wants to maximize classification accuracy
- Turns out this is consistent if the model is not misspecified
- They offer a nice application to investigate the elderly's saving motives.

Gorodnichenko, Y., Pham, T., Talavera, O., 2021. The Voice of Monetary Policy. Working Paper 28592. National Bureau of Economic Research. URL: http://www.nber.org/papers/w28592, doi:10.3386/w28592.

Our features

- Log-mel spectrogram:
  1. For a windowed excerpt, take the Fourier transform of a signal
  2. Map the resulting spectrum onto the mel scale
     - The mel scale is a perceptual scale of pitches judged by listeners to be equal in distance from one another
  3. Take the logs of the the amplitudes at each of the mel frequencies
  4. Returns a matrix of dimension [number of mel scale, number of time windows]
- The Mel-frequency cepstral coefficients (MFCC) are computed by taking additional transformation of the results from 3 and returns a matrix of dimension [number of MFCCs, number of time windows]

Our features (Cont'd)

- Chromagram
  - Mapping the spectrum onto the chroma scale, which we can think of as pitch classes, instead of the mel scale.
  - Returns a matrix of dimension [number of pitch classes, number of time windows]

Return

Hyperparameters

learning rate: 1e-5, batch size: 16 optimizer: RMSprop Epochs: 200

Return