Large Language Models and Machine Learning for Unstructured Data

Lecture 3: Convolutional Neural Networks

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Reading

Background material for the lecture:

1. Chollet, *Deep Learning with Python*, Ch. 8, https://www.manning.com/books/deep-learning-with-python-second-edition
2. James et. al., *An Introduction to Statistical Learning: with Applications in Python*, ch 10.3, https://www.statlearning.com/

Image Classification

Image classification was one of the core problems that drove the growth of deep learning after 2010.

Problem is to correctly identify features of images that have been tagged by humans (e.g. ImageNet).

Image classification is now essentially a solved problem.

The main architecture for the problem is a *convolutional neural network*.

These have 'convolutional' and 'pooling' layers that reduce the dimensionality of images by associating them with learned local features.

Overall Idea [Chollet, 2021]

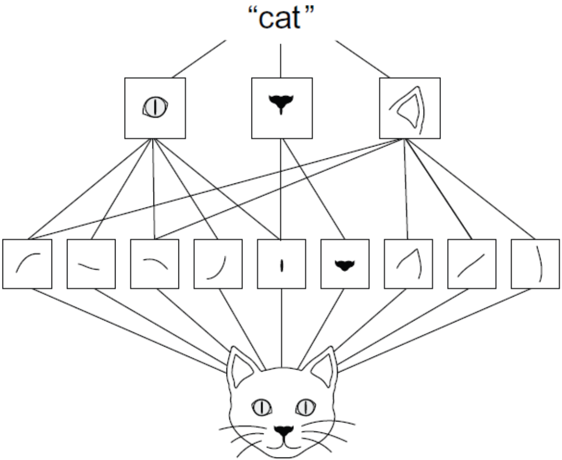


Figure 8.2 The visual world forms a spatial hierarchy of visual modules: elementary lines or textures combine into simple objects such as eyes or ears, which combine into high-level concepts such as "cat."

Example of Convolutional Filter [Chollet, 2021]

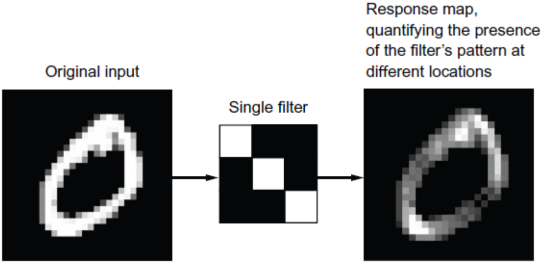


Figure 8.3 The concept of a response map: A 2D map of the presence of a pattern at different locations in an input

Example of (Max) Pooling [James et al., 2023]

$$\text{Max pool} \begin{bmatrix} 1 & 2 & 5 & 3 \\ 3 & 0 & 1 & 2 \\ 2 & 1 & 3 & 4 \\ 1 & 1 & 2 & 0 \end{bmatrix} \rightarrow \begin{bmatrix} 3 & 5 \\ 2 & 4 \end{bmatrix}$$

Overall Architecture [James et al., 2023]

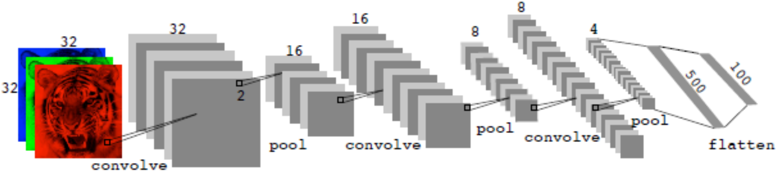


FIGURE 10.8. *Architecture of a deep CNN for the* CIFAR100 *classification task. Convolution layers are interspersed with* 2×2 *max-pool layers, which reduce the size by a factor of 2 in both dimensions.*

Applications of CNNs

Economic Statistics

Measuring economic performance is a precursor for conducting effective economic policy.

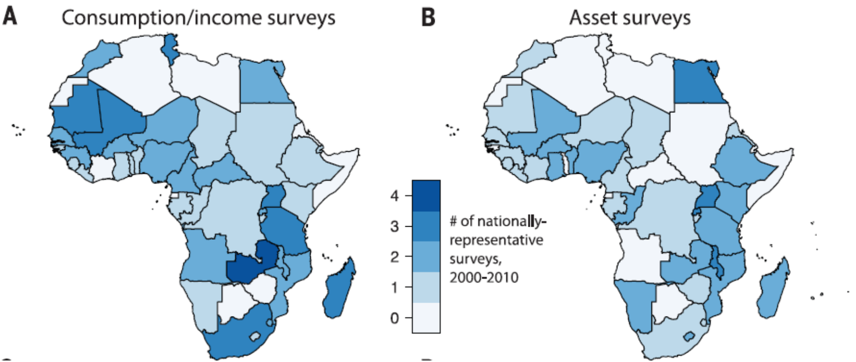
Yet the state of measurement is imperfect, particularly in developing countries.

[Silungwe et al., 2022] report that

1. Half of countries do not publish quarterly GDP statistics from expenditure.
2. 25% of countries (and 50% of African countries) do not conduct a household budget survey.

The cost of increasing survey coverage is enormous, but unstructured data is plentiful.

Survey Coverage in Africa



Measuring Poverty from Satellite Data

[Jean et al., 2016] uses publicly available satellite data to measure poverty at local level in Africa.

Paper adopts a three-step process:

1. Begin with CNN trained on ImageNet data.
2. Update CNN to predict nightlight intensity, which is available at high resolution throughout the world.
3. Use learned features as input into ridge regression for predicting available local spending and asset surveys.

Nightlight intensity does a poor job at capturing variation in expenditure at low levels.

Local features of geography and buildings contain more information.

Filters for Predicting Nightlight Intensity

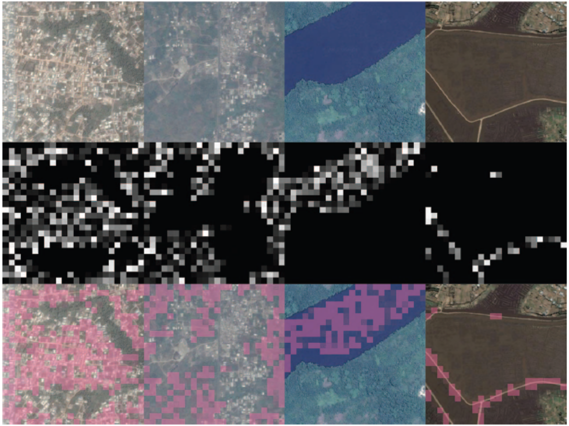
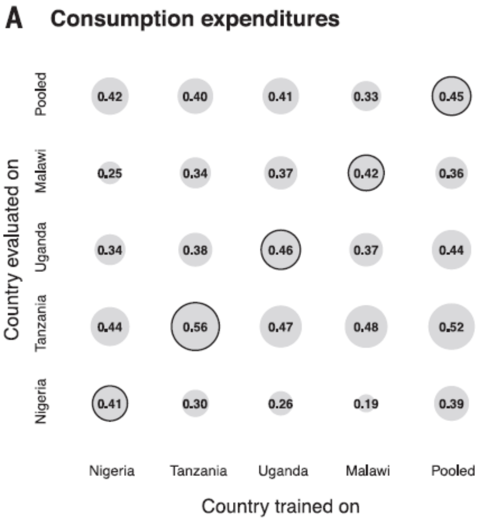


Fig. 2. Visualization of features. By column: Four different convolutional filters (which identify, from left to right, features corresponding to urban areas, nonurban areas, water, and roads) in the convolutional neural network model used for extracting features. Each filter "highlights" the parts of the image that activate it, shown in pink. By row: Original daytime satellite images from Google Static Maps, filter activation maps, and overlay of activation maps onto original images

Generalizability of Ridge Regression



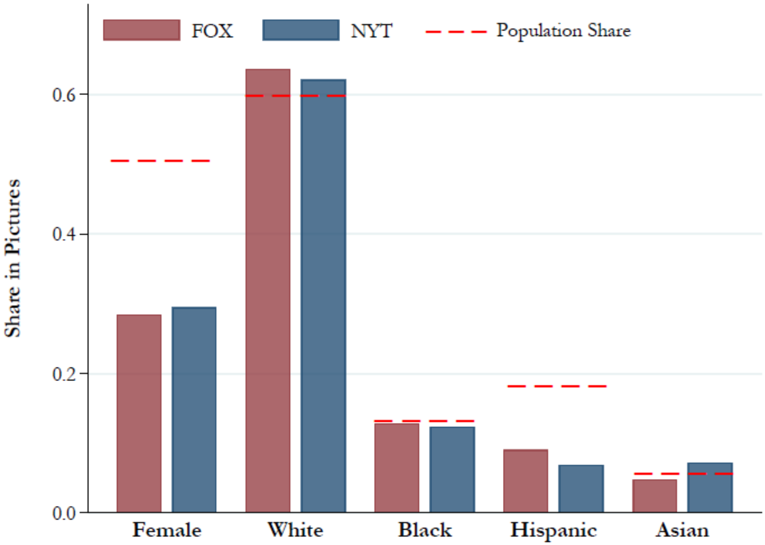
Images in Media Data

[Ash et al., 2022] digitize both text and images from articles in the NYT and Fox News from 2000 through 2020.

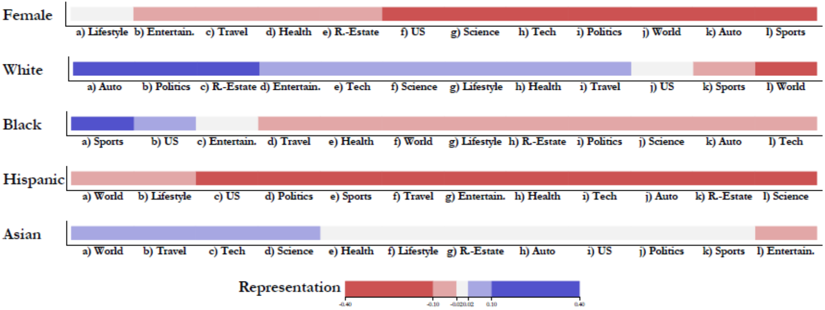
Use publicly available dataset of tagged images to build classifier for gender and ethnicity.

Convolutional neural network for image classification.

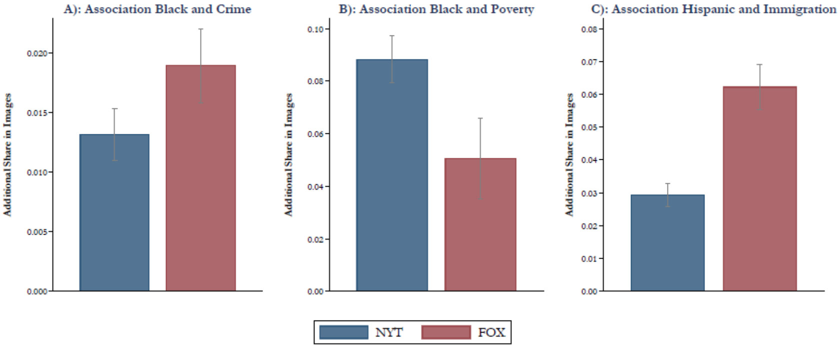
Representation in Media vs Population



Representation in Types of Articles



Association Between Images and Text



Other Applications

[Adukia et al., 2023] explores related ideas in children's books.

[Borgschulte et al., 2021] uses CNN to predict age from CEO photos, correlate with economic distress.

[Mueller et al., 2021] uses CNN to monitor local destruction in Syrian war.

Integrating Text with Images

[Bajari et al., 2023] uses unstructured data from Amazon to revisit the classic problem of hedonic regression (see also related work of [Cafarella et al., 2023]).

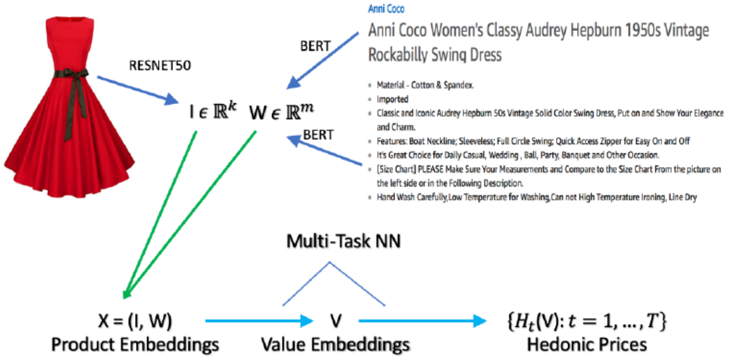
Two sources of data from Amazon ads: (i) image of product; (ii) textual description of product.

Motivation is that unstructed data captures latent attributes of product characteristics that generate utility.

These characteristics can be spanned by text and product embeddings and included in the hedonic regression.

Representation also useful for structural demand estimation [Compiani et al., 2023].

Overview of Method



Results

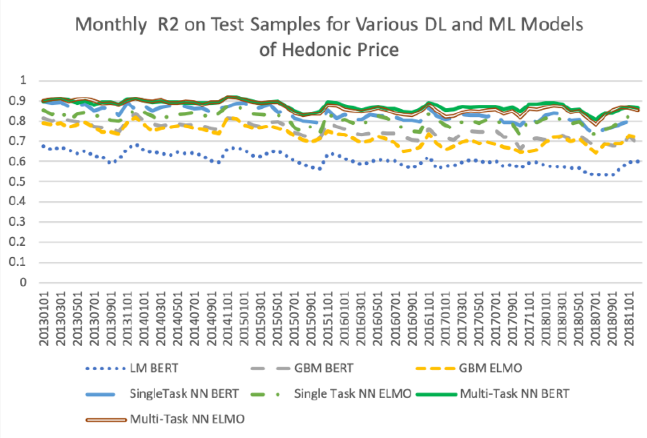


FIGURE 4. The out-of-sample performance of the empirical hedonic price function obtained using neural network every month since March, 2013. Multi-task neural networks dominate singe-task neural networks, which dominate boosted tree models, which in turn dominate linear models.

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