Spatial Clustering of Firms:

A Machine Learning Approach

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Firm Geography

How does the spatial arrangement of firms affect productivity?

What new tools can we use to approach this question?

What can these results tell us about the role of cities in production?

→ We propose a method that utilizes advances in machine learning related to image classification

→ This imposes fewer assumptions and minimizes the loss of information

Density Measures

Traditional methods have used density as a sufficient stastic

- pro: can be run at higher levels of aggregation (city, county, etc)
- con: requires an arbitrary definition of geographic unit

This can be improved by using an **effective** firm density (adding empty land has no effect)

$$\frac{\int_A \rho(x)dx}{\int_A dx} \quad \longrightarrow \quad \frac{\int_A \rho^2(x)dx}{\int_A dx}$$

Characteristic Scale

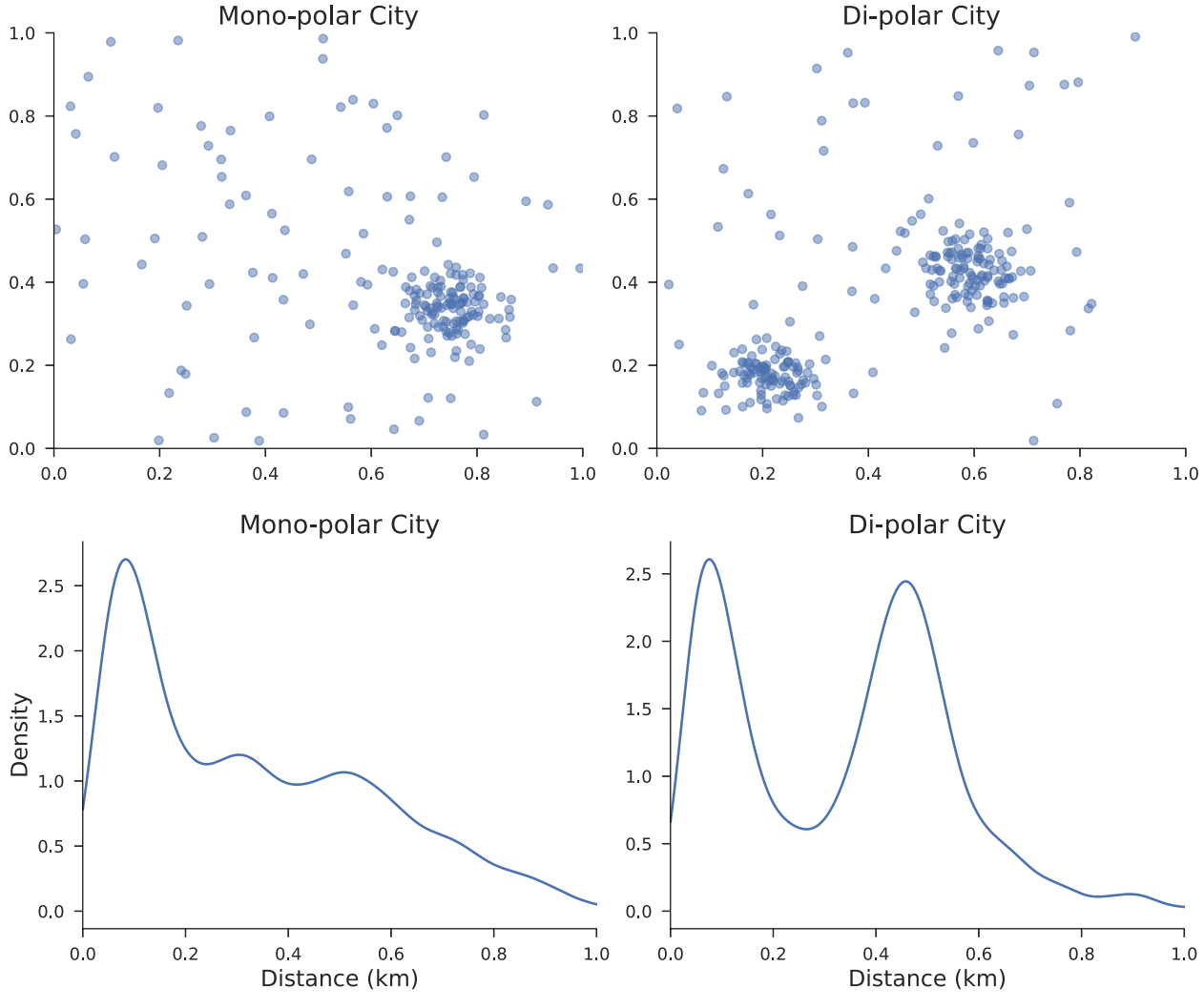
Duranton and Overman (2005) employ a **two-point correlation function** to measure what they call localization

- this is simply the density of distances between pairs of firms (popular in astrophysics)

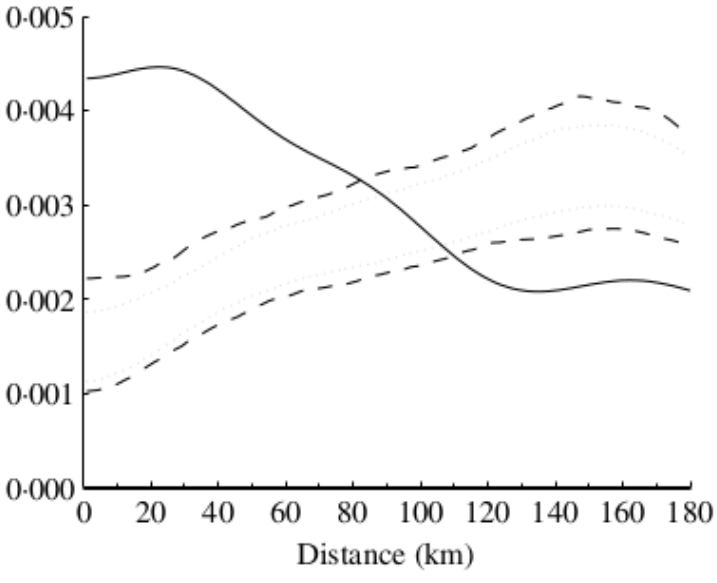
They focus on heterogeneity across industries: each industry has a characteristic distance scale between firms

This (rightly?) compresses radial symmetry (anisitropy) but still throws away a lot of useful information

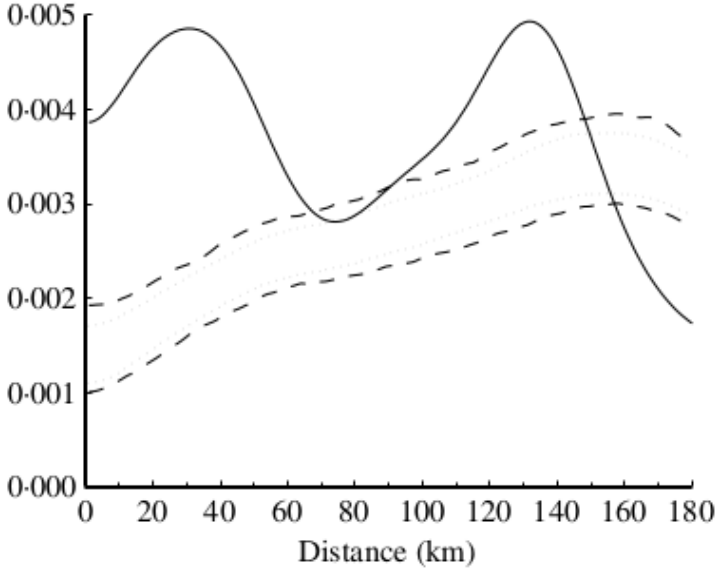
Information Loss



Multiple Poles



(a) Basic Pharmaceuticals (SIC2441)

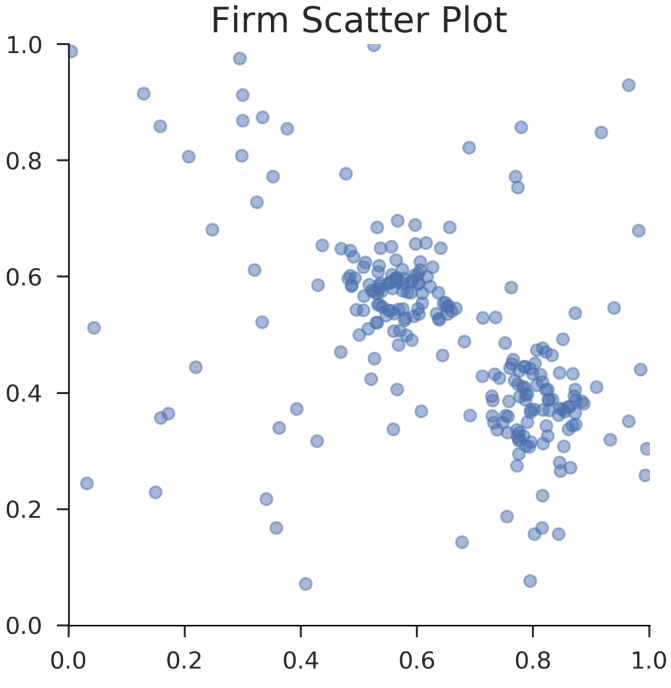


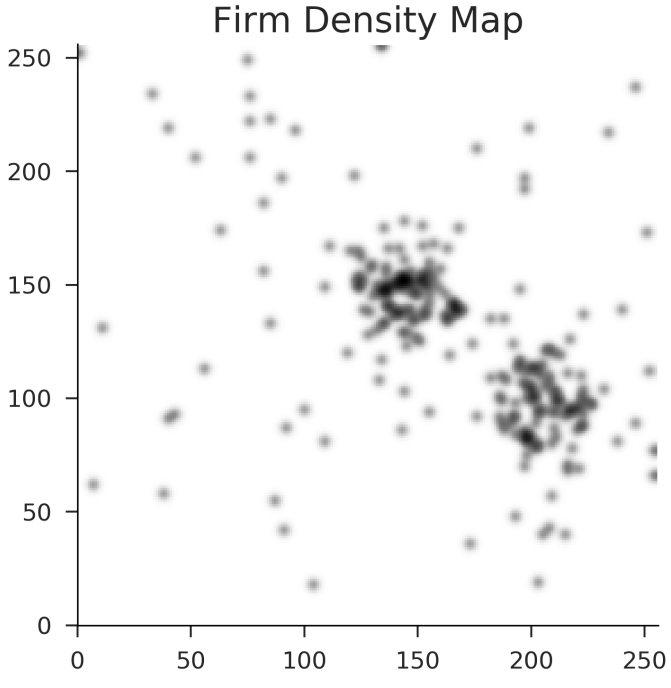
(d) Machinery for Textile, Apparel and Leather Production (SIC2954)

Distributions for pharmaceuticals (left) and textile machinery (right). Pharma is clearly unipolar, while textiles has at least two clusters

Maps and Information

In general, we find that maps are extremely high dimensional objects, but how can we handle this in an economic setting?





Machine Vision

This is a powerful set of tools developed primarily for image classificiation tasks

The canonical example is that of classifying pictures of hand-written digits (0—9) into their corresponding number

- users include post offices, banks, etc
- major training datasets include MNIST and CIFAR

Digit Classifier (MNIST)

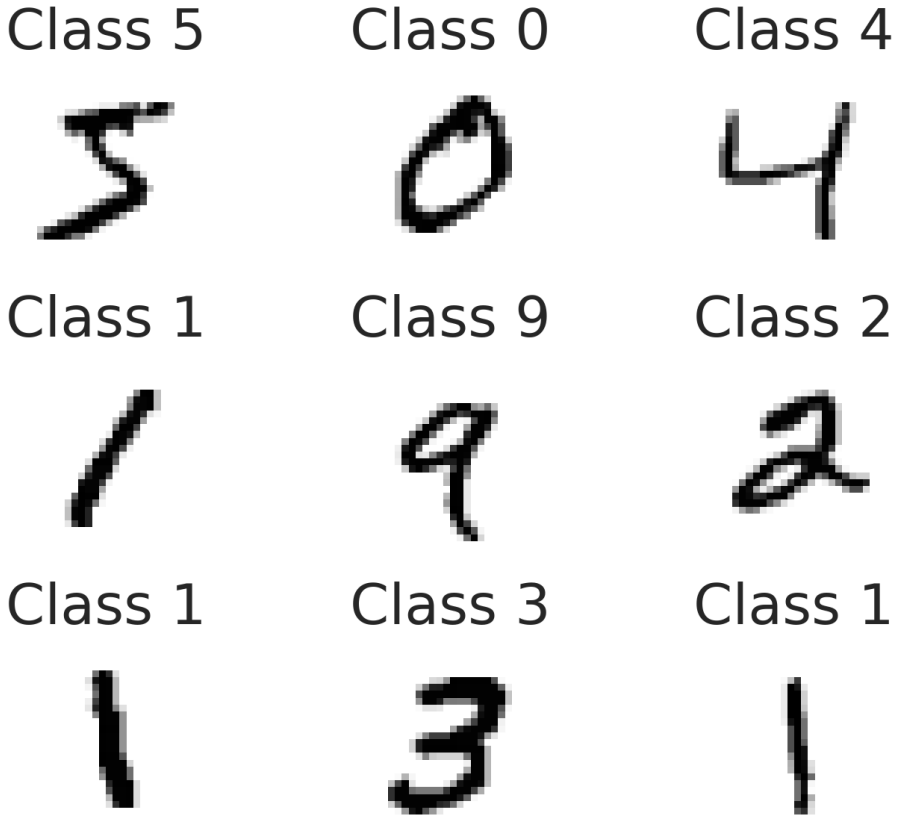
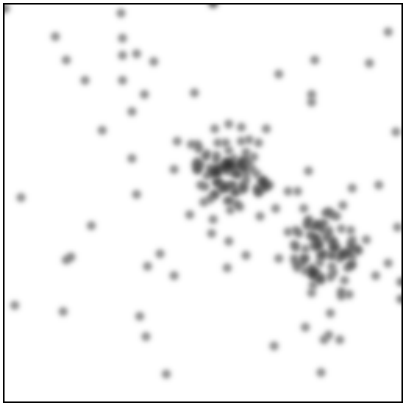


Image Classifier (CIFAR-10)

Application to Maps

We can apply these to maps by rasterizing their continuous density into a grid of pixels ($\mathbb{R}_+^{N \cdot N}$)

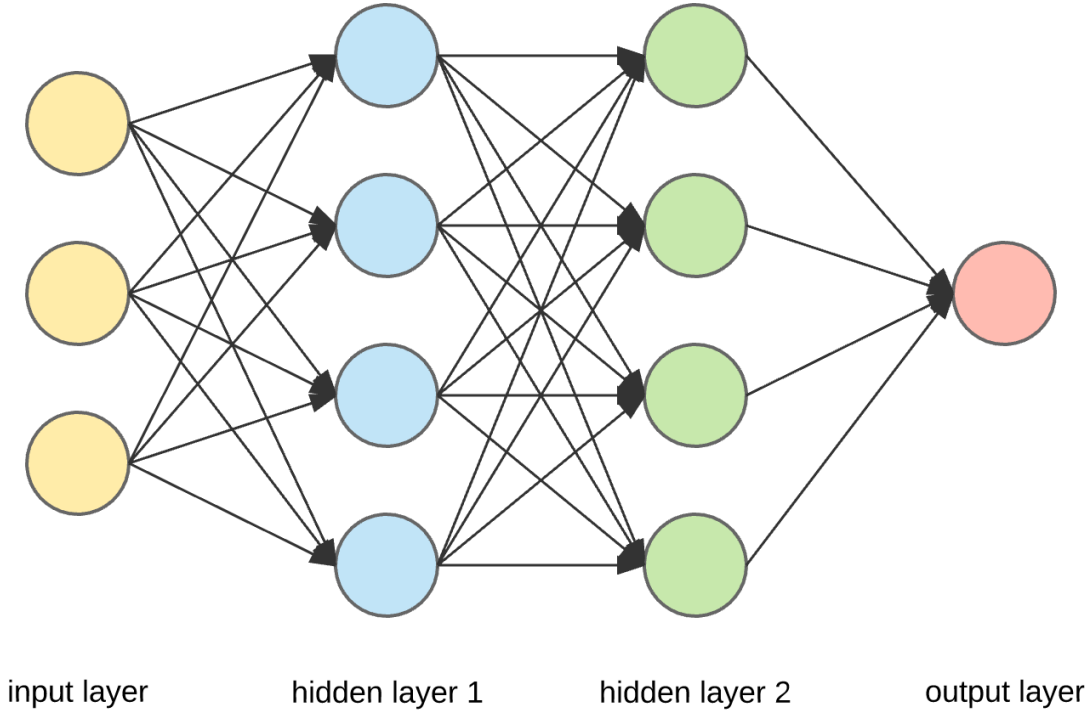


$\longrightarrow$ Productivity

Instead of classifying them into digits, we instead want to predict other properties of firms represented therein (like productivity or growth)

Neural Networks

Neural networks (NN) consist of a network of cells, each of which performs a simple operation on the data



Source: Towards Data Science

Network Cells

Inputs ("X data") are fed in and through the network to generate outputs ("Y data")

Each cell applies an "activation function" (F) to a linear sum of its inputs

$$y = F\left(W \cdot x + b\right)$$

Training a network involves choosing parameters (W and b) to minimize an objective function

- mean-squared error for real value data or categorical cross-entry for categorical data

Cell Activation Zoo

Multinomial probabilities (softmax)

$$z = W \cdot x + b \quad \rightarrow \quad y_k = \frac{\exp(z_k)}{\sum_{k'} \exp(z_{k'})}$$

Rectified linear unit (relu)

$$y = \max\{0, W \cdot x + b\}$$

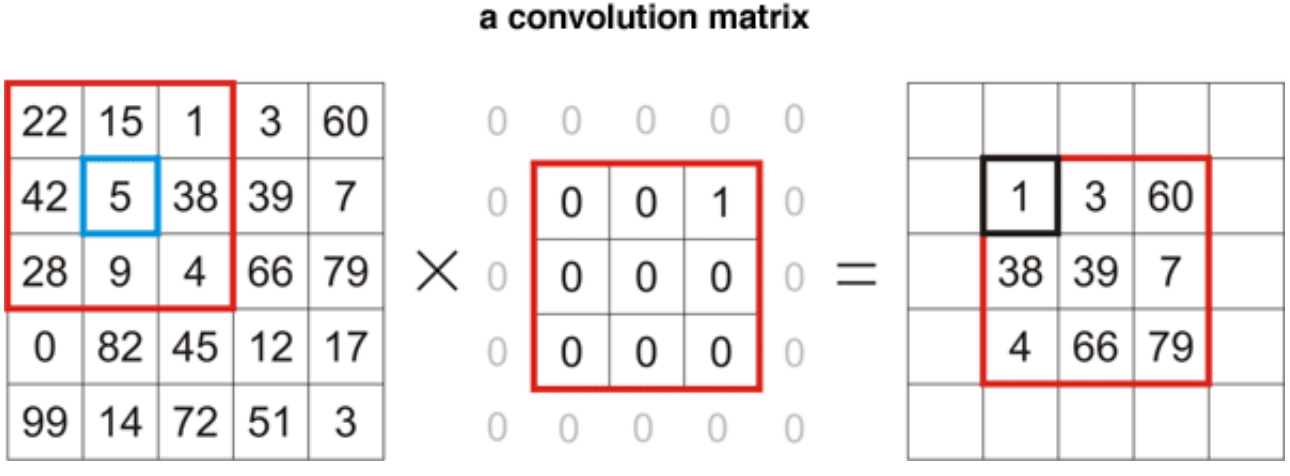
Sign activation (tanh)

$$y = \tanh(W \cdot x + b)$$

Convolution Cell

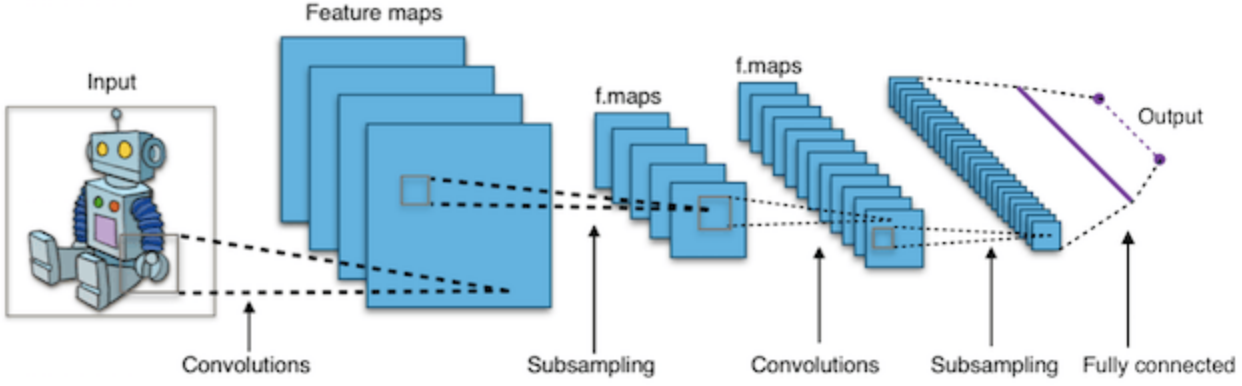
These aggregate local information and can detect small features line a border or a corner

- examples include blurring (averaging), contrast, flow, etc



Source: Designing What's Next

Convolutional Networks



Source: Elite Data Science

The primary feature of CNNs is that they exploit translational symmetry at small spatial scales.

Image is reduced with successive steps of convolution and pooling, then finally classified with a dense network.

Complexity and Overfitting

Massive number of parameters from high-level layers (MNIST: 407k, CIFAR10: 890k)

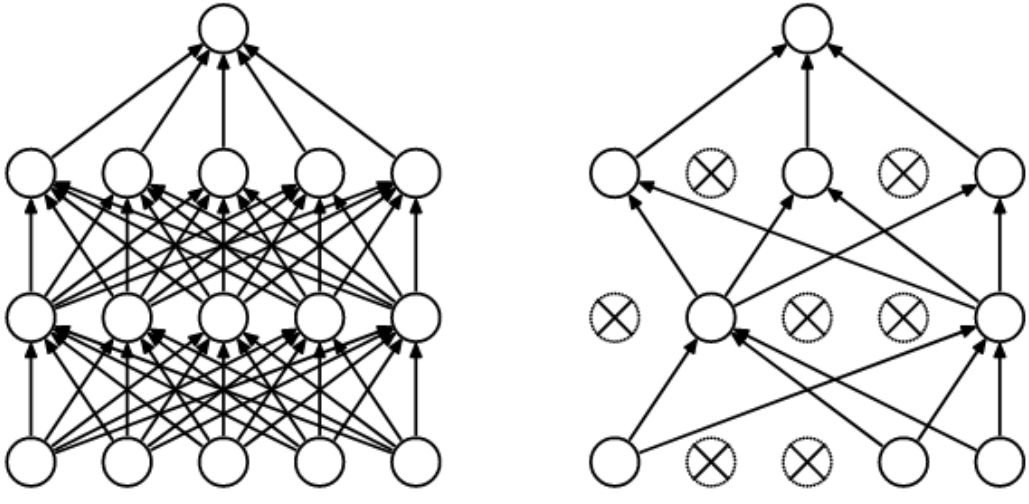
- even with millions of obervations, we run the risk of overfitting

Classical ML technique for preventing overfitting is to separate out a fraction (say 20%) of the data as a validation set

- don't train on this, just test predictions afterwards
- if validation error starts rising, we are probably overfitting

Dropout Techniques

Srivastava et al (2014) proposed a revolutionary method for preventing overfitting: **dropout** randomly severs connections in the network while training

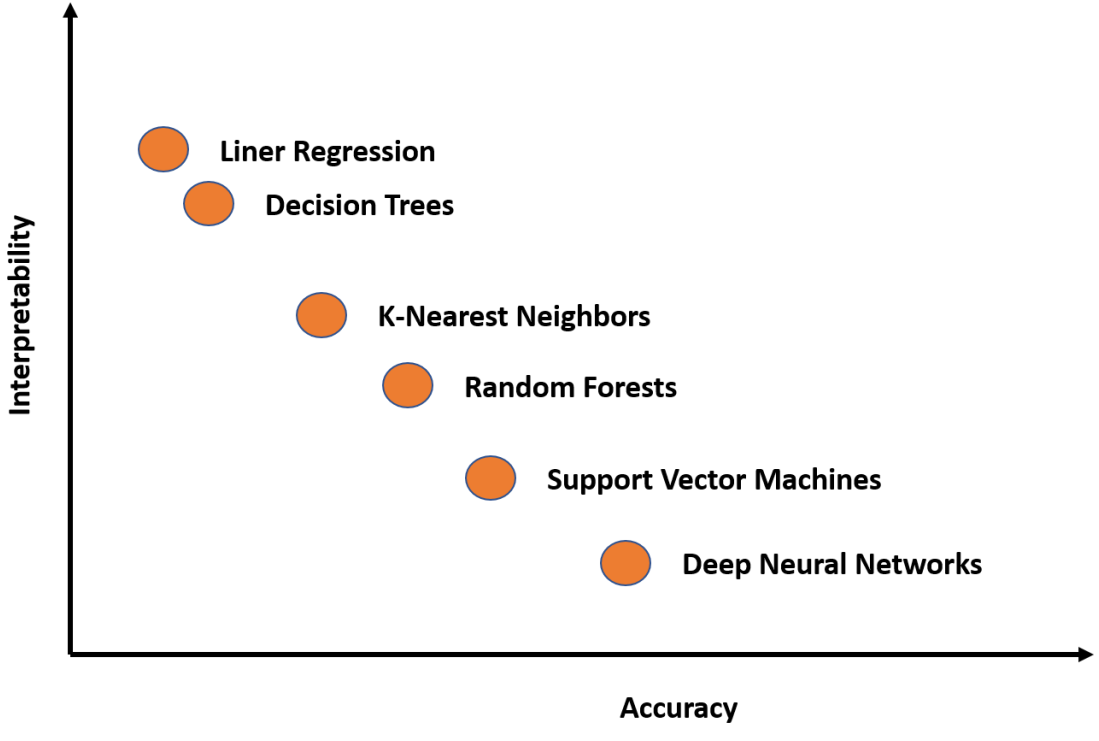


(a) Standard Neural Net (b) After applying dropout.

Source: Srivastava et al (2014)

Algorithmic Tradeoff

In the high accuracy regime of neural networks, understanding mechanism of "black box" is difficult



Source: Towards Data Science

Existing Literature

Engstrom, Hersh, and Newhouse (2017): predicting poverty and consumption levels in Sri Lanka from satellite imagery

- not end-to-end: use ML to extract features like cars and buildings, then feed into regression analysis

Large literature using night time lights (NTL) to predict poverty and GDP using traditional techniques (Henderson, Storeygard, and Weil, 2012)

Data Sources

Economic Census (NBS) of Chinese firms in the year 2004

- includes both manufacturing and services
- roughly 1.4 million firms in total

Firm level fields available

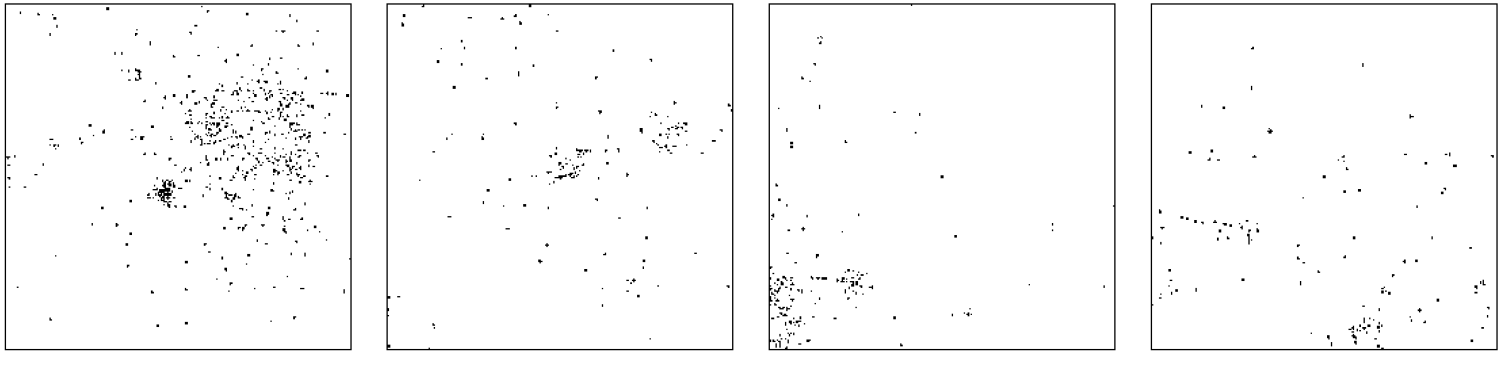
- street address → geo coordinates using Baidu API
- categorical data: industry code and province
- balance sheet info: income, assets, employees
- currently unused: age and firm type

Density Maps

The density map is firm specific: it is the density map centered on the firm for a given radius

- we use both 2km and 8km radii with 256 pixels
- due to measurement error, we add blurr of ~30m

Final output is 256x256 monochrome 8-bit JPEG image file for each firm (1.4 million) and each radius



Classical Method

Using the same density maps, we can aggregate into concentric rings: 0-2km, 2-4km, 4-8km

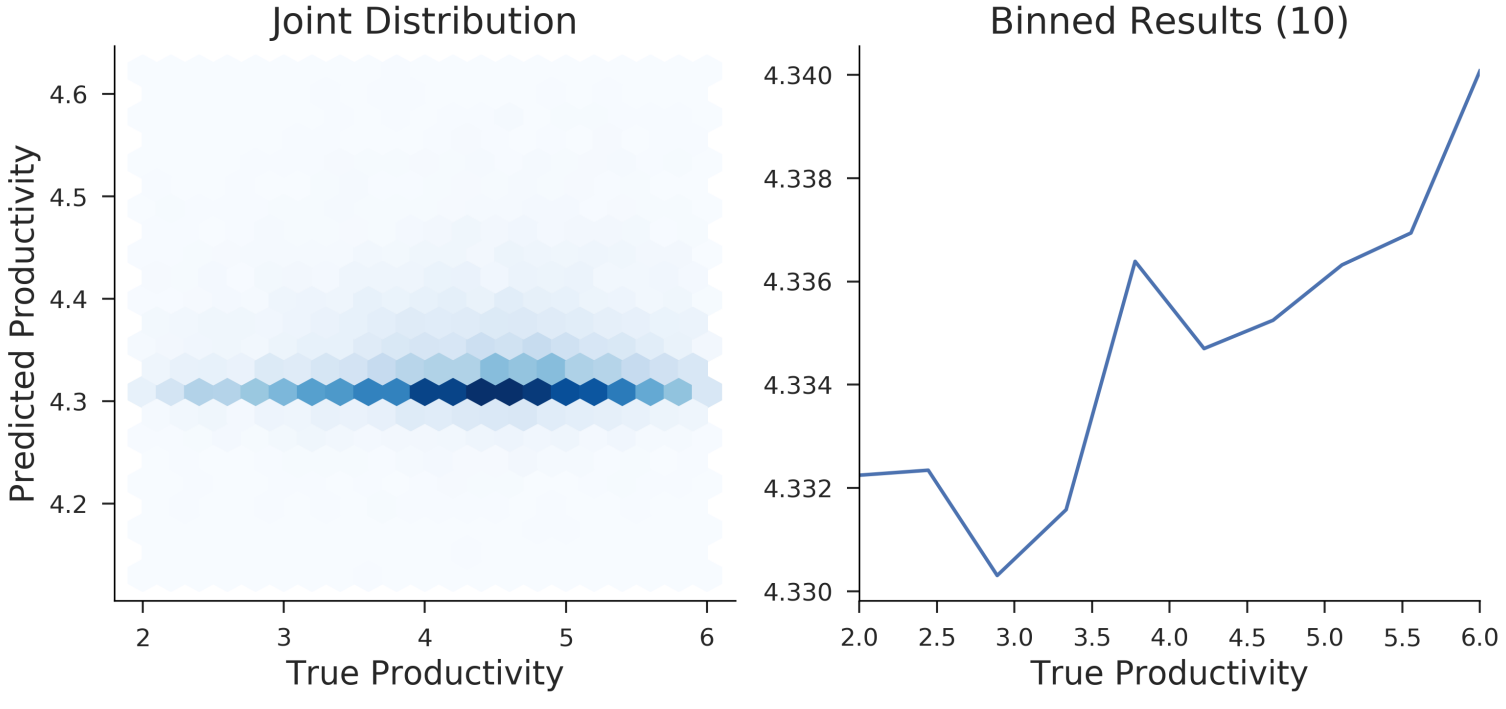
$$\log(p_i) \sim 1 + d_{0-2} + d_{2-4} + d_{4-8}$$

Coefficients for d_{0-2} and d_{2-4} are insignificant, while d_{4-8} is significant and positive

Variable	Coefficient	Std Err	P-value
1	4.29	0.01	0.00
d_{0-2}	-6.09	37.4	0.87
d_{2-4}	14.2	24.2	0.56
d_{4-8}	11.7	5.38	0.03**

Classical Results

Results have low predictive power and show little variation across true productivity bins



Computational Tools

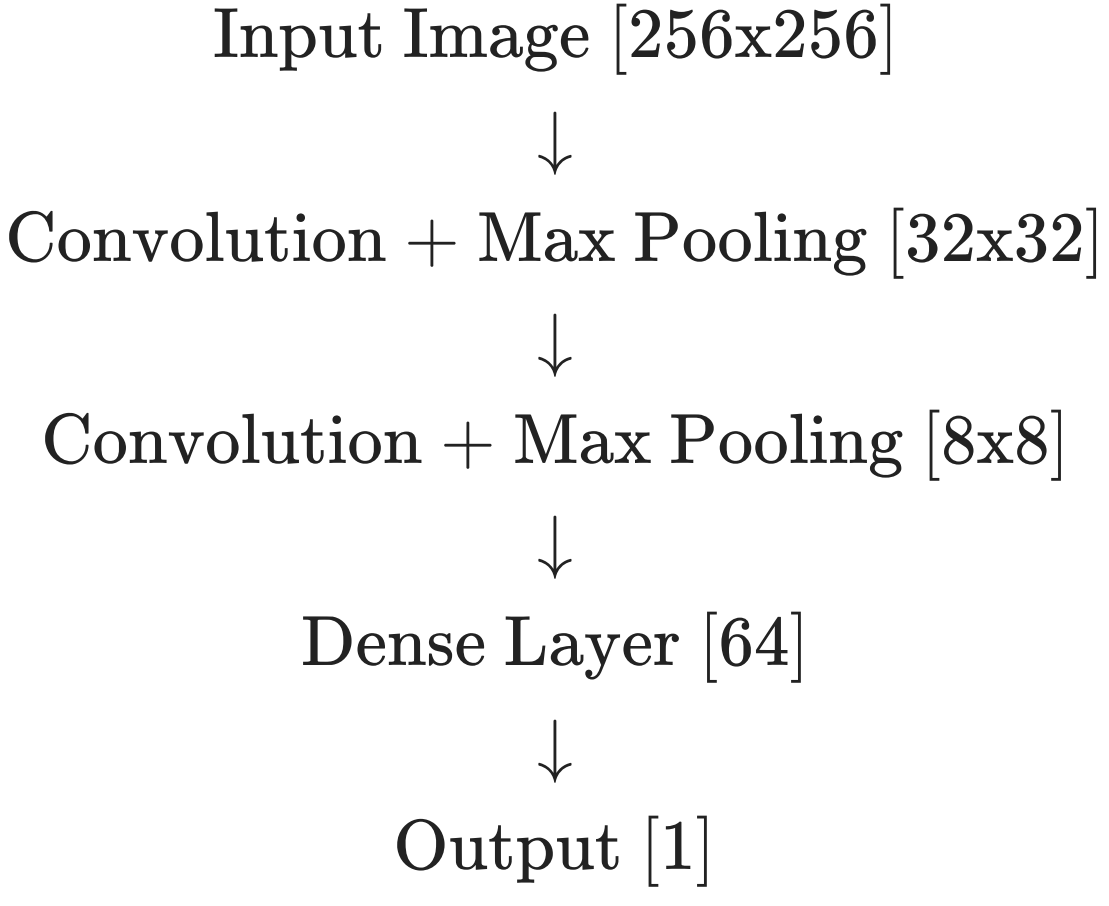
Recent renaissance of machine learning tools: Tensorflow (Google) and Torch (Facebook)

- higher level APIs such as Keras make network construction simple

```
model = keras.models.Sequential([
    keras.layers.Flatten(input_shape=(28, 28)),
    keras.layers.Dense(512, activation=tf.nn.relu),
    keras.layers.Dropout(0.2),
    keras.layers.Dense(10, activation=tf.nn.softmax)
])
```

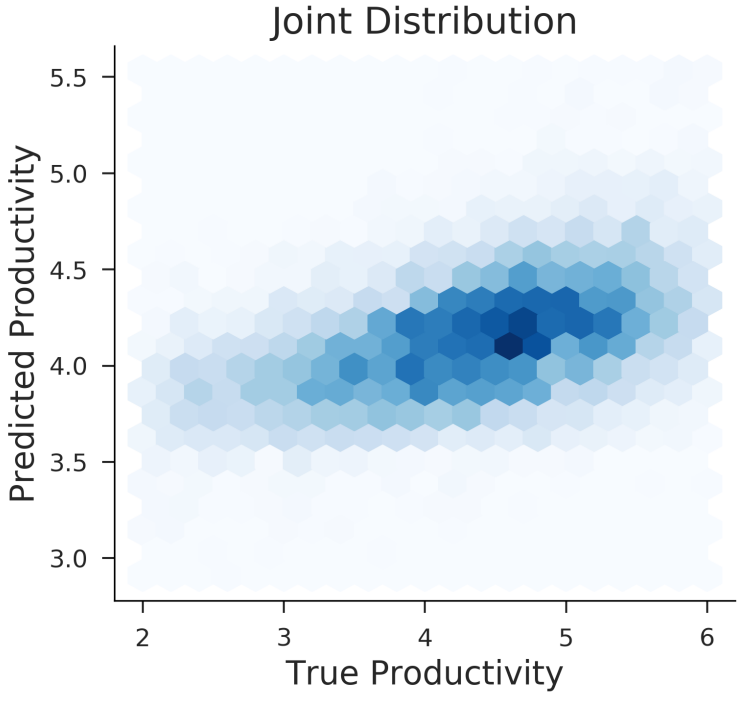
Only need to specify objective (categorical cross entry) and optimizer (gradient, adam, etc) and ready to train

CNN Network Structure



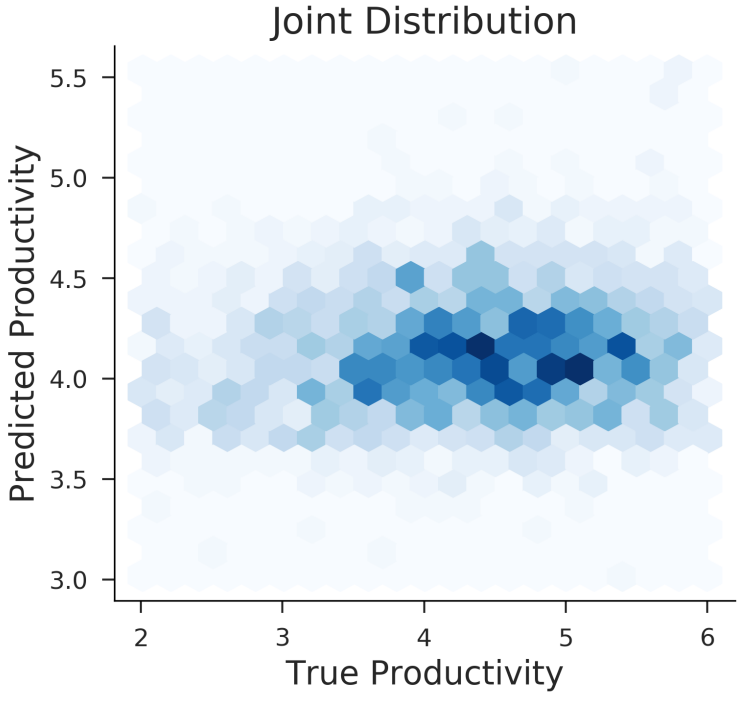
CNN Results

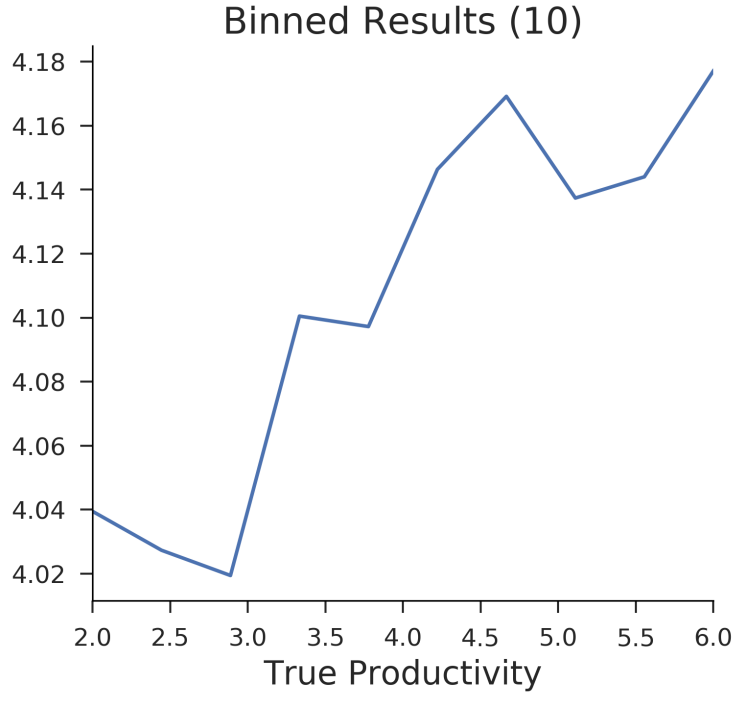
Same objective as classical case (log productivity) using mean squared error as the objective and the `adam` optimizer for 25 epochs



CNN Validation

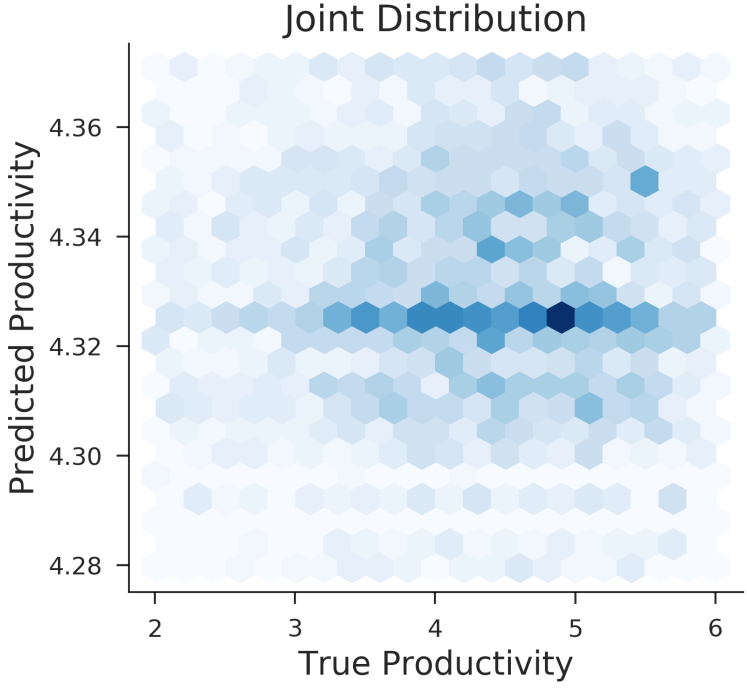
Inspecting validation numbers reveals a sustained effect but also some overfitting

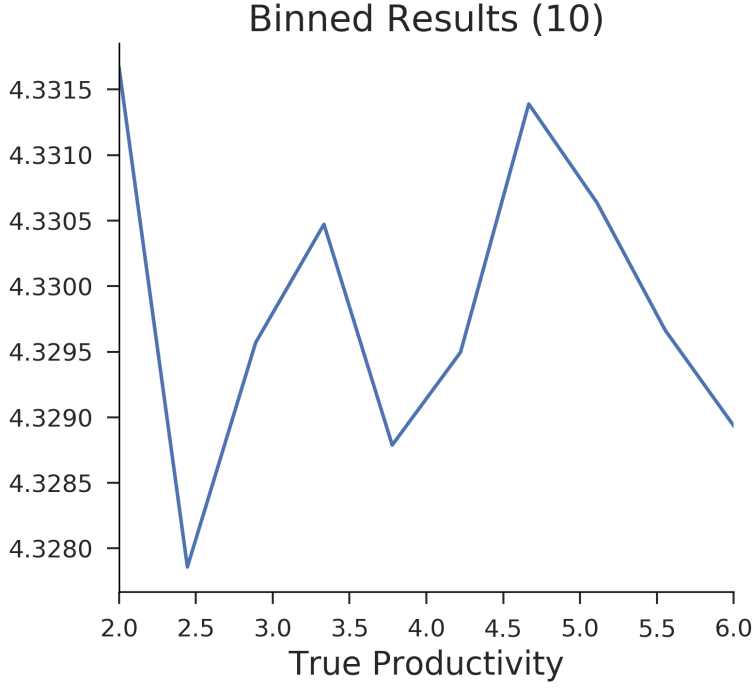




Intermediate Results

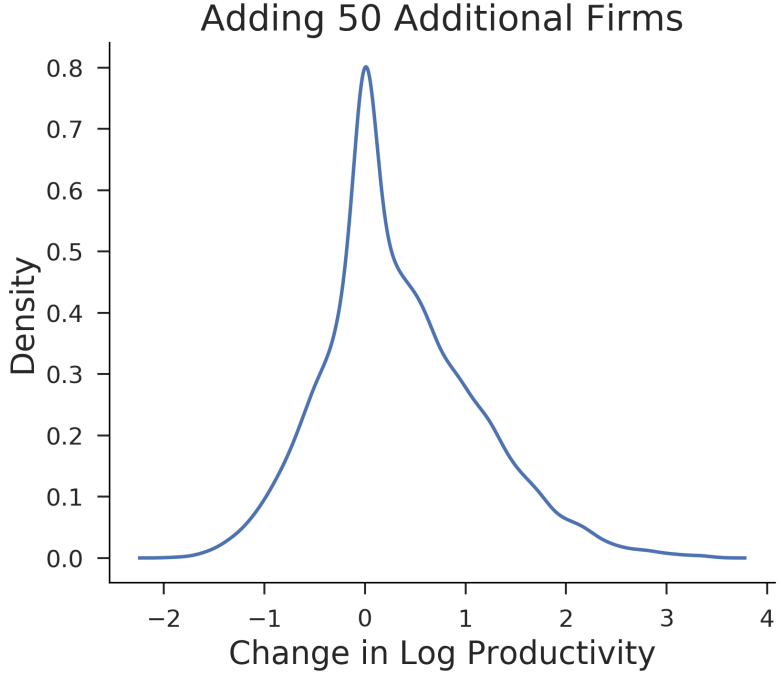
To bridge the gap between classical (OLS) and CNN, we can look at a simple radial model (where the radius is trained rather than fixed). This appears to have little predictive power.





Impulse Responses

To understand effect of spatial clustering, we take each original firm and add in new firms artificially, then plot change in log productivity (average is ~0.5)



Endogeneity Issues

Up to now, we focused on prediction, but in terms of inference there is an endogeneity issue

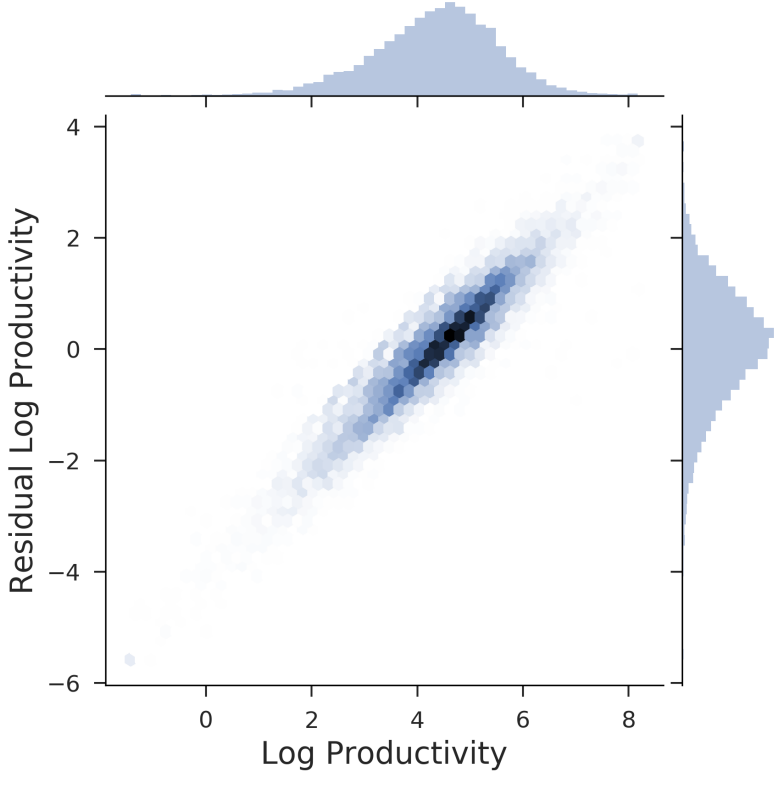
- there are potential confounders, firm location choice is endogenous

In terms of observable characteristics, there are two approaches

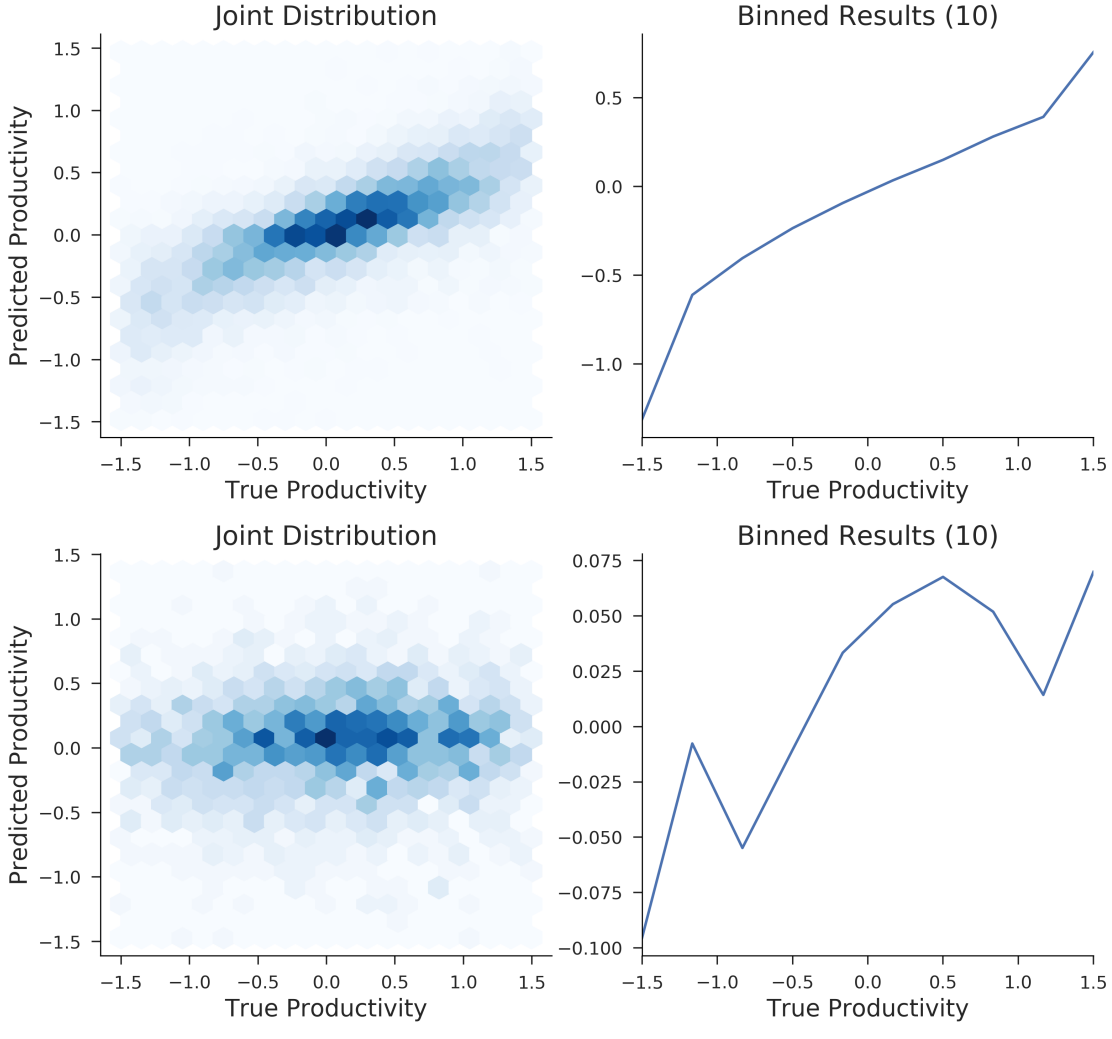
1. partial out industry/province fixed effects and predict residual
2. feed additional firm features directly into neural network

Residual Productivity

Partialling out fixed effects from industry code (4-digit) still leaves a substantial amount of correlated variation



Residual Results



Intrumental Variables

Here we can adapt a standard instrumental variables approach as well

- two steps: prediction and inference

Example instrument: distance to ancient provincial capital

- prediction: estimate mapping from distance to density map
- inference: use predicted density map as input into productivity

Additional Inputs

Currently we use only the density map of firms at various radii

- worker density (weighted by employee count)
- only within industry (or weighted upstream/downstream)

Satellite imagery or other maps to explicitly account for features like hills, mountains, rivers, etc.

Future Work

Use patent data from SIPO to understand the spatial clustering of innovation, which might be even more interesting

Perform same analysis using US data and compare results. Does the differential structure of cities affect firm producitvity substantially?