



## USING NATURAL SHAPE STATISTICS OF URBAN FORM TO MODEL SOCIAL CAPITAL

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**Abstract.** The social aspect is an important but often overlooked part of sustainable development philosophy. In hoping to popularise and show the importance of social sustainable development, this study tries to find a relation between the social environment and urban form. Research in the social capital field provided the methodology to acquire social computational data. The relation between human actions and the environment is noted in many theories, and used in some practices. Human cognition is computationally predictable with natural shape analysis and machine learning methods. In the analysis of shape, a topological skeleton is a proven method to acquire statistical data that correlates with data collected from human experiments. In this study, the analysis of urban form with respect to human cognition was used to acquire computational data for a machine learning model of social capital in counties in the USA.

**Keywords:** urban form, natural shape statistics, social capital, machine learning, multi-layer perceptron regressor.

### Introduction

Physical space certainly limits human behavior. Buildings are designed to trade freedom of movement for safety and comfort. Being in a build environment brings humans closer, leading to collaboration or conflict. Shape of the environment could make some influence to the direction of the relationship.

Spatial influence in some migrating animals is so predictable that it allows us to construct logic gates (Gunji *et al.* 2012). Space syntax allows us to predict pedestrian concentrations and crime (Jiang, Claramunt 2002; Matijošaitienė *et al.* 2013). Transportation and social interaction are parts of human interaction. Crime is one extremely negative measurement of the social environment, but there are others. Social capital is one example. For those unfamiliar with the term, it is associated mostly with social activity and collaboration.

There have been attempts to connect social capital with space syntax. It has also been shown to be influenced by the availability of green spaces (Maas *et al.* 2009).

This paper tries to reveal the connection between statistically measured proprieties of the shape of buildings and human behaviour expressed as social capital.

Correlation is widespread method to show connections between phenomena captured by data, however today there are more techniques provided by machine learning

field. Not all methods are good for every problem. To find connection between social capital and urban form, the same or similar methods were used as in cited references used for theoretical justification.

In the study, statistical data is collected from the OpenStreetMap database, and transformed to statistical data and analysed with a science kit for Python. It is shown that the shape of the buildings itself has an influence on social capital. By using a Multi-layer Perceptron regressor, it was possible to predict social capital with 69.5% accuracy.

### Related work

Many thinkers and creators have noticed the influence of the surroundings on human behaviour. Actions are simply provoked by the function of surrounding objects (Corbusier, Cohen 1923). Distorted mental maps influence path selection (Lynch 1960). Variety of proportion inspires social interaction (Whyte 1980). The wrong number and proportion of decorations can induce anxiety and illness (Salingeros, West 1999).

An increase in computational power available sprouted the practices based on the theories formulated earlier. The number of pedestrians was predicted with space syntax (Hillier 2015). City expansion was predicted with cellular automata (Li, Yeh 2000).

Some interesting theories relating to architecture and cognition, arguing that a perceivable history of surroundings can influence health, do not yet have practical tools (Leyton 2012). Similar theories less related to architecture have been used successfully to prove the relation between human cognition and the statistical analysis of shape (Wilder *et al.* 2011).

## Social capital

In this paper, social capital is based on Putnam's theory, but there are other social capital alternatives available.

Social capital is an old, loosely defined term to describe the value obtainable from social interactions. Many definitions of social capital have been made. There are some notable overviews of social capital definitions (Adler, Kwon 2002).

Some social capital theories analyse social capital as a network of connections (Licamele, Getoor 2006; Rutten *et al.* 2010; Sampson, Graif 2009; Smith, Giraud-Carrier 2010; Subbian *et al.* 2013). The problem with this view is that in some approaches it is difficult or impossible to reliably find connections, although recent papers solved this by data mining social networks (Smith, Giraud-Carrier 2010).

Despite being 100 years old (Hanifan 1916), the term social capital does not have a well-established definition. Authors are constantly improving their understanding of the essence and practical usage of the term. There are even studies of the evolution of the definition of social capital (Adler, Kwon 2002). The following subsections are an analysis of social capital based on different viewpoints.

The first usage of the term social capital was in the context of education (Hanifan 1916). This aspect is periodically revisited by (Kovanovic *et al.* 2014; Licamele, Getoor 2006; Misra *et al.* 2013). The most popular aspect is civic engagement (Adler, Kwon 2002b; Horst, Toke 2010; Kovanovic *et al.* 2014; Nguyen *et al.* 2013; Putnam 2000; Rutten *et al.* 2010; Sampson, Graif 2009; Svendsen 2010; Turner-Lee 2010; Wilson 2006). It is also worth mentioning trustworthiness (Adler, Kwon 2002; Bourdieu 2011; Kawachi *et al.* 1997; Rutten *et al.* 2010). A recent trend in land development is noticeable (Chen *et al.* 2015; Martinkus *et al.* 2014).

Also, the possibility that dimension names or measurement units are mostly newly invented with every publication as the definition of social capital is also adjusted for the needs of the research. Despite the dissimilarity in the chosen dimension names, most authors find that social capital is multidimensional.

Authors opinions differ according to the conception of what is measured with the properties of social capital. Some state that social capital is the propriety of a person (Bourdieu 2011; Kovanovic *et al.* 2014; Licamele, Getoor 2006; Nguyen *et al.* 2013) for others, the propriety of a network or location (Sampson, Graif 2009; Smith, Giraud-Carrier 2010; Wilson 2006).

Bourdieu (2011) points out that social capital is only a subtype of unified capital. In his theory, there are three subtypes of capital: economic, cultural and social. Conversions are possible between subtypes. Social capital has a propriety "volume", which is measured in the size of mobilisable network connections. The ability to accumulate and maintain social capital correlates with the size of the capital of all subtypes. He distinguishes economic capital as the root of other subtypes. Economic capital may be not the easiest to measure. He also shows that spare time is an indication of capital of all subtypes.

Most popular subtypes are the bridging and bonding first developed by Putnam (1995), and later used by many authors with different approaches. Bonding refers to personal connections which are maintained by some form of communication by individuals who share similar interests. The bridging connection is between individuals who know each other, but have few or no common interests, so communication is not maintained, but can usually be used for business opportunities.

A notable analysis of virtual social networks uses bridging and bonding connections of social capital to construct two types of network: Implicit Affinity Networks (IAN) and Explicit Social Networks (ESN). Members of IAN share many common interests. Members of ESN are less related, just by useful contacts in other fields (Smith, Giraud-Carrier 2010).

The traditional method to measure social capital is the survey.

Participating in surveys could be an indication of a participant's available free time. This could be linked to an indication of Social Capital itself as discussed in Bourdieu (2011). It also applies to taking part in virtual social networks. A contrary refusal to participate in surveys or low virtual social network participation could indicate low social capital.

Virtual networks are not always dissocialised. There are properties of connections between members of a network. Individuals can gain benefits from social capital, but they also have to invest in order to be used by other members of the network to maintain their connections. Some authors report negative effects called "paradox of embeddedness" (Huysman, Wulf 2004).

The page rank algorithm based on the theoretical work of Pinski and Narin (1976) patented by Stanford University and used widely in search engines was used by Licamele and Getoor (2006); Subbian *et al.* (2013) to evaluate curatorship in scientific papers.

The least squares regression method of mathematical function fitting published by Adrien-Marie Legendre in 1805 was used to determine the relationship between the death rate and income inequality (Kawachi *et al.* 1997).

Smith and Giraud-Carrier (2010) use Python library “pyrfeed” to gather blog entries. They also use MALLET’s implementation of LDA (Natural Language Processing) to construct IAN. Networks are drawn using the “Organic” layout in the Cytoscape 2.6.0 software package. Latent Dirichlet allocation is a way of automatically discovering topics that these sentences contain (Hoffman *et al.* 2010).

Licamele and Getoor (2006) construct a Friendship-Event Network from a database of science paper co-authorship, and use it to predict participation in a given conference in a given year with SVM. Support Vector Machines are machine learning models for data classification and regression analysis (Verikas, Gelžinis 2003).

## Method

For social capital data, a readily available database was used (Rupasingha *et al.* 2006). Here, social capital follows Putnam’s theory (Putnam 2001). The database consists of input variables, including numbers of religious organisations, civic and social associations, business associations, political organisations, professional organisations, labour organisations, bowling centres, physical fitness facilities, public golf courses, sports clubs, population, voter turnout, census response rate, number of non-profit organisations not including those with an international approach, and final computed value of social capital index. It covers states in the USA, with the exception of Alaska. It has an entry for every county in each available state, with a total of 3,108 entries (Fig. 1). This database defined the territorial area and the structure of the research.

To be able to use the social capital database together with the results of building shape analysis, buildings had to be analysed in the same territories, or counties. The US Census Bureau provides Congressional District Cartographic Boundary Shapefiles (Geography 2017). They provide GIS data projected in North America – NAD83

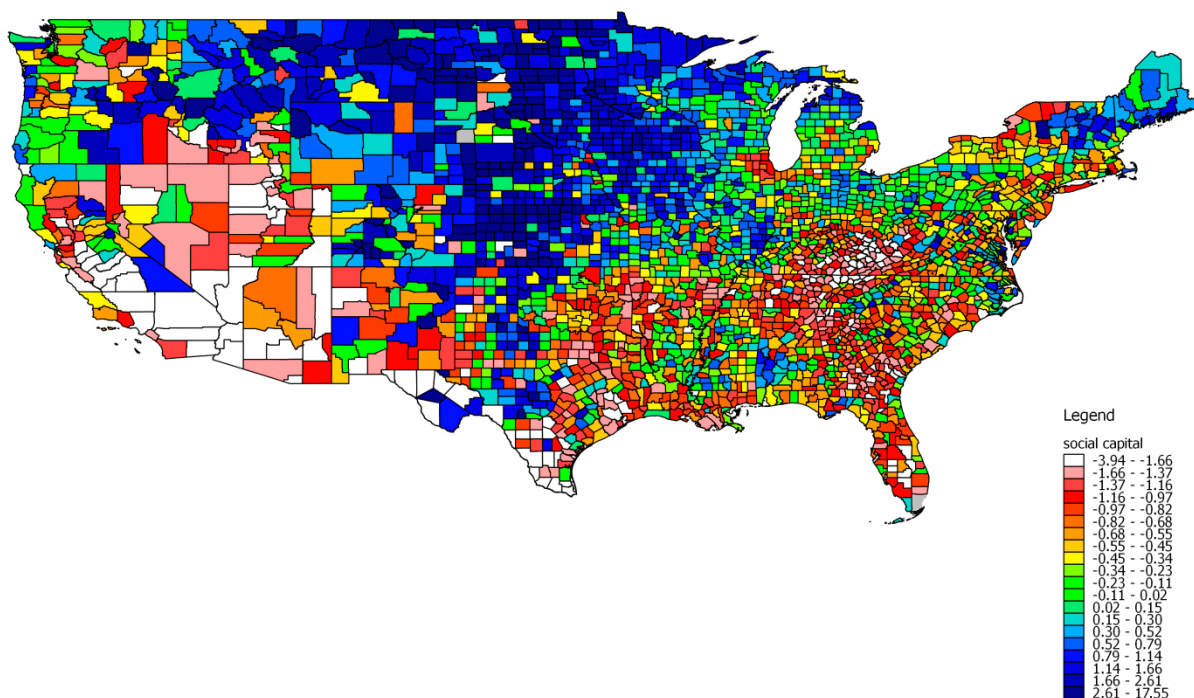


Fig. 1. Social capital of USA counties

projection, and (OpenStreetMap 2017) provides data World Geodetic System WGS84 projection. To achieve compatibility, the county boundary data was re-projected using an open source software package (QGIS 2017). OpenStreetMap data was not downloaded directly from the service, instead the North American data extract in one file was used, kindly provided by (Geofabrik 2017). Cutting into county boundaries and filtering building data was done with an open source software tool (Osmosis 2017). Due to the large size of the data file (169 GB), cutting was very slow. To increase speed, precuts were made to a bounding box covering all state boundaries. To get the state boundaries, a dissolve tool was used in QGIS. To get bounding box coordinates, a special script was written using (OSGeo 2017) library in (Python 2017). Osmosis needs a special “.poly” file format to be able to cut by polygon. County boundaries were exported to poly using specialised plug-in in QGIS. A skeleton generation algorithm used by (Wilder *et al.* 2011) is the custom and not available. Judging from the description given in (Feldman, Singh 2006), it would be computationally too expensive in this application. Therefore, for the skeleton computation (SFCGAL 2017), an extension to (PostGIS 2017) was chosen. The skeleton implementation in SFCGAL is based on (Aichholzer, Aurenhammer 1996; Eppstein, Erickson 1998;

Felkel, Obdržálek 1998; Laycock, Day 2003). Osmosis has integration into PostGIS, which was used to upload building polygons into the PostGIS database. To compute the skeletons, the ST\_StraightSkeleton function of SFCGAL in PostGIS was used. Following the structure of data from files to database tables at this point, one table in the database holds information of all the building skeletons in one county (Fig. 2).

Information about skeleton nodes is kept inside a single cell in the database entry. A special function in PostGIS was developed to explode a single skeleton into a table consisting of entry per node and extract analytical parameters. The parameters described in (Wilder *et al.* 2011) can be summarised as a network analysis of skeleton, and does not have open source libraries to compute. Several customised variants of the (Dijkstra 1959) path finding algorithm were implemented which collect all the parameters along its execution. It first initiates depth parameter with a number of nodes in the skeleton, and then starts at multiple nodes which are dead ends of the skeleton network, and follows to find the deepest node in the skeleton, writing steps taken from the dead end into a depth parameter, in case it has a bigger value than the steps taken. From this, it is possible to calculate the maximum and mean depth of the skeleton. Then it starts at the deepest node, and steps through nodes

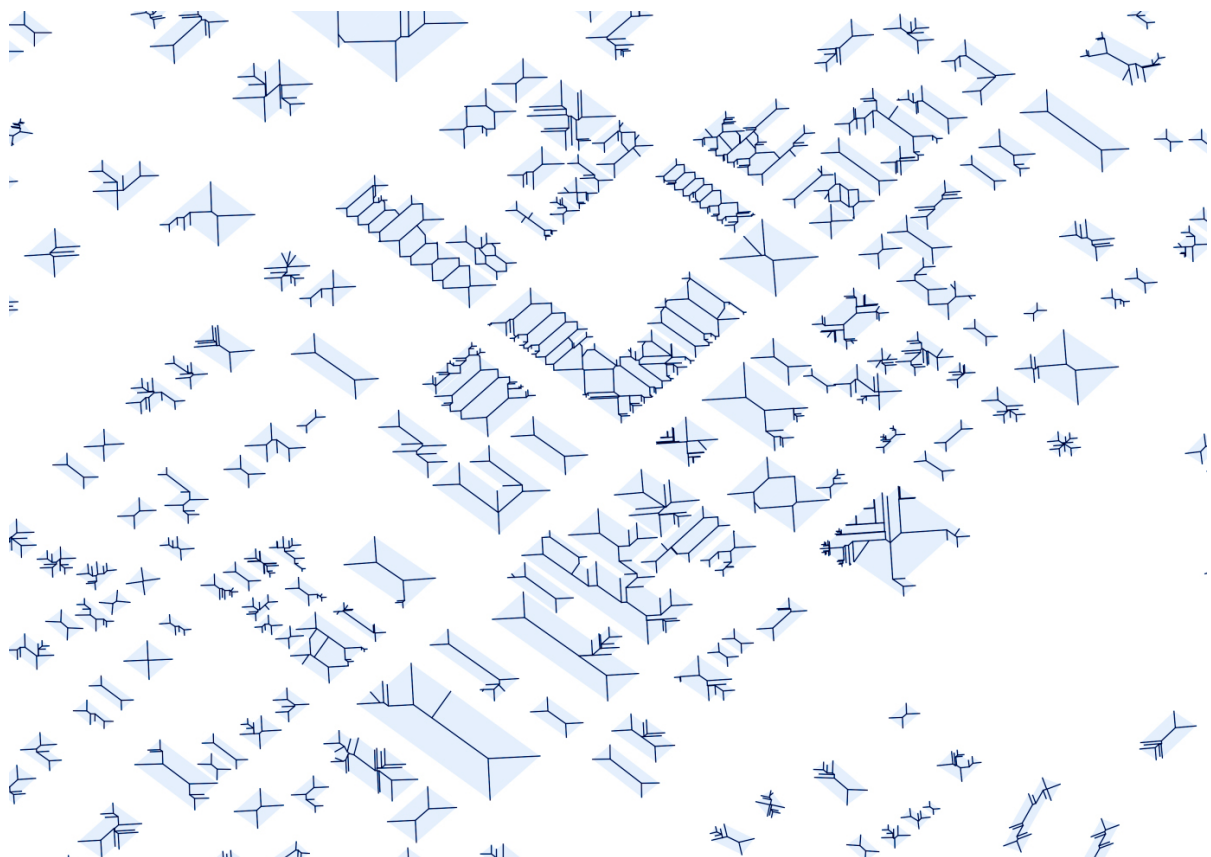


Fig. 2. Building polygons and skeletons

calculating the number of branches it encounters and the angles between nodes. From these values, it is possible to calculate the maximums and means of the following parameters: the number of nodes connected to a given node, the length of the node, the azimuth of the node, the turn angle between nodes, the absolute turn angle between nodes, and the branch depth. Also, the total number of branches and “wiggles” of the skeleton. Later, the dividing sum of all turn angles is calculated by the sum of absolute turn angles. The skeleton generation algorithm used in (Wilder *et al.* 2011) allows skeleton optimisation, but the SFCGAL implementation used in this study does not have any tunable parameters. To compensate, the approach proposed in (Bai *et al.* 2007) was used. The skeleton nodes with minimum depth were dropped, and the calculations were repeated collecting parameters in a separate set. The pruned skeletons have a deeper topology and no spurious branches (Fig. 3).

Unfortunately, due to the time constraints of this project, only maximum and mean values of the number of nodes and depth were used in the analysis phase. Also, only 744 counties were processed in the skeleton parameter collection phase (Fig. 4). At this point, there is a collection of parameters per building, although to connect to social capital data it is necessary to have parameters per county. To reduce the entries, a bucket sort algorithm is used (Cormen

*et al.* 2009). It increases the number of parameters based on maximum value. The resulting database consisted of 116 parameters.

For the analysis of the data, the open source package (Anaconda 2017) was used. Naturally, there were many small buildings with simple shapes, and progressively less as the shape complexity increased. Salingaros, West (1999) argue that an environment which does not follow rules of universal scale and universal distribution negatively affects health. These rules are better known as the power law (Faloutsos *et al.* 1999). Could it also affect social capital? To test this theory, collection parameters generated with a bucket sort algorithm were fitted with a toolbox for testing if the probability distribution fits the power law (Alstott *et al.* 2014). This fitting was done for every county per parameter. The fitted models produce four additional parameters representing how well the parameter distribution fits the power law. The resulting database consisted of 179 parameters.

To show connection between data parameters one can tune weights and values of machine learning model by exposing it to data. Ability to represent data of fine tuned model can be measured by calculating difference between data and prediction, also referred as error. Several models were fitted to test if it is possible to predict social capital

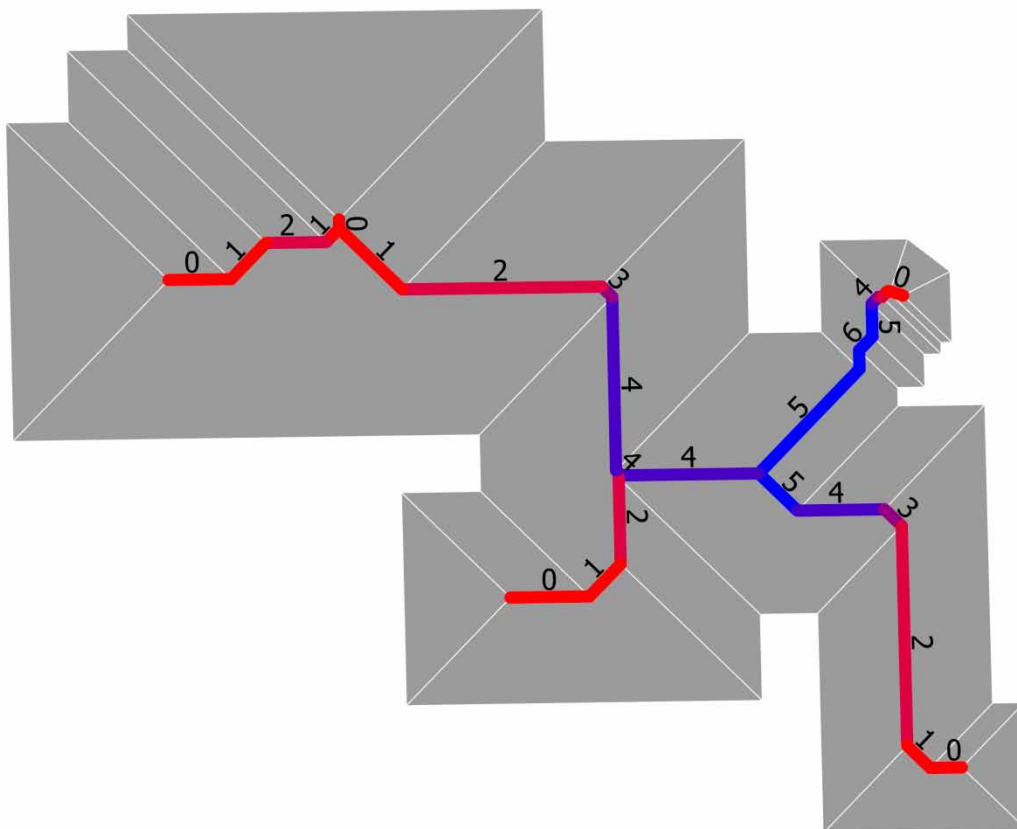


Fig. 3. Pruned skeleton (red-blue) colours and numbers represent skeleton depth

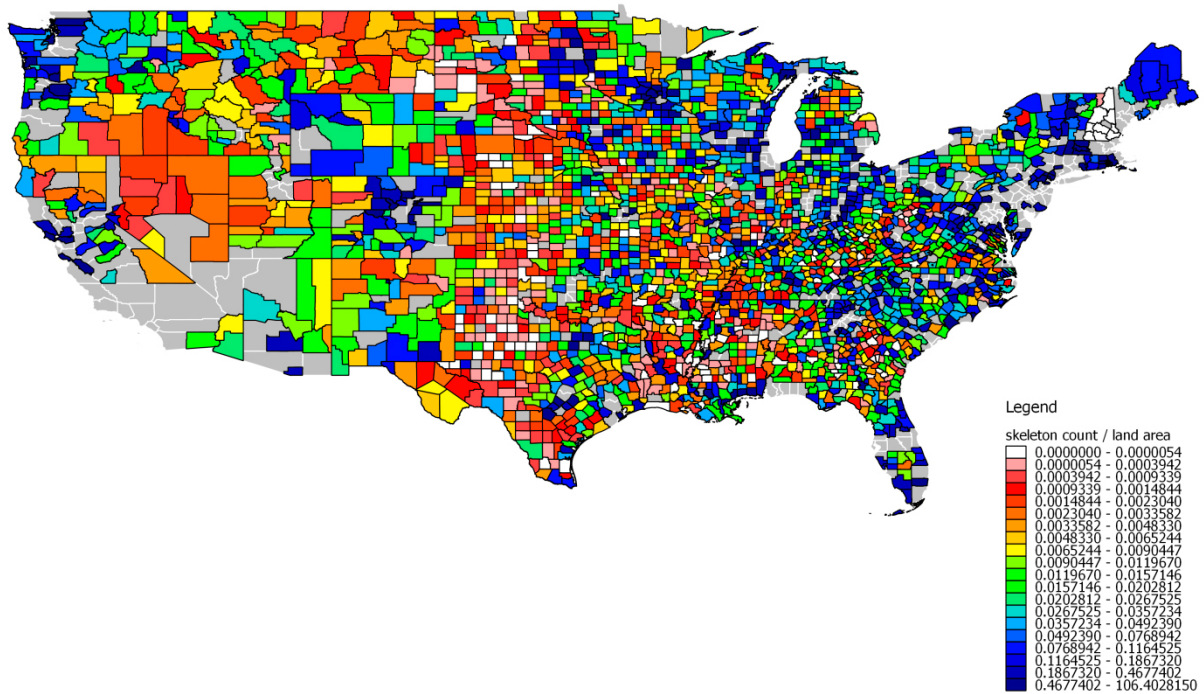


Fig. 4. Skeleton data available per county

from a statistical analysis of building skeletons. To measure the model performance, the R-squared method was used (Cameron, Windmeijer 1997). As the most simple and best-known model, the least squares regression was used as a benchmark for other models (Geladi, Kowalski 1986). It was impossible to use the naive Bayes classifier as in (Wilder *et al.* 2011) due to the incompatibility of problem type. Instead, the Bayesian ridge model was used, as it is based on the same theory (Park, Casella 2008). Lastly, a Multi-layer Perceptron regressor was used (Geladi, Kowalski 1986). A combination of hyperbolic activation function and quasi-Newton solver showed the best results. It was possible to further increase predictions by eliminating some parameters with a forward selection algorithm (Koller, Sahami 1996).

## Results

Table 1. Comparison of model results

model	R-squared
least squares regression	0.115
Bayesian ridge	0.016
Multi-layer Perceptron regressor (some tuning)	0.489
Multi-layer Perceptron regressor with hyperbolic activation function and quasi-Newton solver	0.548
Multi-layer Perceptron regressor with hyperbolic activation function and quasi-Newton solver after parameter elimination	0.695

Every model in Table 1 was tested comparing target data – social capital index to predicted values by the model. Performance of the models varied. To be able to compare predictions, unified method to calculate error hat to be chosen. There are multiple ways to calculate prediction errors. R-squared method to calculate prediction errors tends to be used quite often. Its popularity could be explained by the fact that it is comparison of two models in itself. It works by comparing errors of prediction to average of target values:

$$R^2 = 1 - \frac{\sum (y - y_p)^2}{\sum (y - y_a)^2},$$

where  $y$  is target value,  $y_p$  is predicted value of model,  $y_a$  is average of all target values.

By comparing calculated R-squared values of tested models not only it is possible to compare models between themselves but to measure connection of the data.

It is evident that the Bayesian ridge did not make better predictions than the simplest model; nevertheless, it was better than the simple averaging of values, as the result is positive.

The multi-layer Perceptron regressor result shows enough evidence to support the continuation of this research.

These results cannot be treated as final or scientifically sound, because the predictions were made on the same data on which the model was trained. Nevertheless, it shows that

a connection between social capital and building statistical analysis is present, and must be investigated further.

## Conclusions and further work

The state of this ongoing research shows promising preliminary results.

The primary goals are to complete parameter gathering on all counties, better fine tune models of hyper parameters, and measure the results using cross validation (Kohavi 1995).

Further improvements could be made by taking into account the properties of surrounding buildings, and measuring the properties of skeletons computed from the space between buildings.

Parameter elimination process will offer further insights to which properties of skeletons influence social capital index. This could be used for building design guidelines for maximizing social capital.

Trained model could be used on projects to predict the social capital they would generate.

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## SOCIALINIO KAPITALO MODELIAVIMAS TAIKANT PASTATŲ FORMOS STATISTINĘ ANALIZĘ

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Santrauka

Tvarios plėtros teorijoje socialinė aplinka yra pripažinta kaip svarbus veiksnys, tačiau trūksta praktinės metodikos. Ryšio tarp urbanistinės formos ir socialinės aplinkos radimas aktualizuotų ir padėtų populiarinti socialinę tvarią plėtrą. Aplinkos įtaka žmonių tarpusavio elgesiui yra ne kartą aptartas reiškinys, tačiau praktikoje retai taikomas. Ankstesniuose socialinio kapitalo tyrimuose pateikiamos metodologijos ir statistiniai duomenys esamos situacijos analizei atlikti. Kaip žmonės suvokia formas, yra nuspėjama taikant statistinę formos analizę ir dirbtinio intelekto metodologiją – sistemos mokymąsi. Klasifikuojant formas topologinio skeleto metodologija gaunami rezultatai koreliuoja su duomenimis, surinktais per eksperimentą, kuriame žmonės klasifikuoja formas. Taikant žinomas formos analizės metodologijas, atspindinčias suvokimą, buvo surinkti duomenys modeliuoti socialinį kapitalą su sisteminio mokymosi modeliu. Sisteminis mokymasis yra dirbtinio intelekto sritis, kurioje remiantis pateiktais duomenimis automatiškai sukalibrojujama kompleksinė matematinė formulė. Modeliuojant socialinį kapitalą su formos skeleto statistiniais duomenimis, geriausi rezultatai pasiekti taikant neuroniniais tinklais pagrįstą sisteminį mokymąsi.

**Reikšminiai žodžiai:** urbanistinė forma, formos analizė statistiniais metodais, socialinis kapitalas, sisteminis mokymasis, daugiasluoksnis perceptronas.