On Move Pattern Trends in a Large Go Games Corpus

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***Abstract*—We process a large corpus of game records of the board game of Go and propose a way of extracting summary information on played moves. We then apply several basic data-mining methods on the summary information to identify the most differentiating features within the summary information, and discuss their correspondence with traditional Go knowledge. We show statistically significant mappings of the features to player attributes such as playing strength or informally perceived "playing style" (e.g. territoriality or aggressivity), describe accurate classifiers for these attributes, and propose applications including seeding real-work ranks of internet players, aiding in Go study and tuning of Go-playing programs, or contribution to Go-theoretical discussion on the scope of "playing style".**

***Index Terms*—Board games, Evaluation, Function approximation, Go, Machine learning, Neural networks, User modelling**

I. Introduction

THE field of Computer Go usually focuses on the problem of creating a program to play the game, finding the best move from a given board position [1]. We will make use of one method developed in the course of such research and apply it to the analysis of existing game records with the aim of helping humans to play and understand the game better instead.

Go is a two-player full-information board game played on a square grid (usually 19×19 lines) with black and white stones; the goal of the game is to surround the most territory and capture enemy stones. We assume basic familiarity with the game.

Many Go players are eager to play using computers (usually over the internet) and review games played by others on computers as well. This means that large amounts of game records are collected and digitally stored, enabling easy processing of such collections. However, so far only little has been done with the available data. We are aware only of uses for simple win/loss statistics [2] [3] and "next move" statistics on a specific position [4] [5].

Additionally, a simple machine learning technique based on GNU Go's [6] move evaluation feature has recently been presented in [7]. The authors used decision trees to predict whether a given user belongs into one of three classes based on his strength (causal, intermediate or advanced player). This method is however limited by the blackbox-use of GNU Go engine, making it unsuitable for more detailed analysis of the moves.

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We present a more in-depth approach — from all played moves, we devise a compact evaluation of each player. We then explore correlations between evaluations of various players in the light of externally given information. This way, we can discover similarity between move characteristics of players with the same playing strength, or discuss the meaning of the "playing style" concept on the assumption that similar playing styles should yield similar move characteristics.

We show that a sample of player's games can be used to quite reliably estimate player's strength, game style, or even a time when he/she was active. Apart from these practical results, the research may prove to be useful for Go theoretists by investigating the principles behind the classical "style" classification.

We shall first present details of the extraction and summarization of information from the game corpus (section II). Afterwards, we will explain the statistical methods applied (section III), and then describe our findings on particular game collections, regarding the analysis of either strength (section IV) or playing styles (section V). Finally, we will explore possible interpretations and few applications of our research (section VI) and point out some possible future research directions (section VII).

II. Data Extraction

As the input of our analysis, we use large collections of game records in SGF format [8] grouped by the primary object of analysis (player name when analyzing style of a particular player, player rank when looking at the effect of rank on data, etc.). We process the games, generating a description for each played move – a *pattern*, being a combination of several *pattern features* described below.

We compute the occurence counts of all encountered patterns, eventually composing n-dimensional *pattern vector* $\vec{p}$ of counts of the n (we use $n = 500$) globally most frequent patterns (the mapping from patterns to vector elements is common for all generated vectors). We can then process and compare just the pattern vectors.

A. Pattern Features

When deciding how to compose the patterns we use to describe moves, we need to consider a specificity tradeoff — overly general descriptions carry too few information to discern various player attributes; too specific descriptions gather too few specimen over the games sample and the vector differences are not statistically significant.

We have chosen an intuitive and simple approach inspired by pattern features used when computing Elo ratings for candidate patterns in Computer Go play [9]. Each pattern is a combination of several *pattern features* (name–value pairs) matched at the position of the played move. We use these features:

- capture move flag,
- atari move flag,
- atari escape flag,
- contiguity-to-last flag[1] — whether the move has been played in one of 8 neighbors of the last move,
- contiguity-to-second-last flag,
- board edge distance — only up to distance 4,
- and spatial pattern — configuration of stones around the played move.

The spatial patterns are normalized (using a dictionary) to be always black-to-play and maintain translational and rotational symmetry. Configurations of radius between 2 and 9 in the gridcular metric[2] are matched.

Pattern vectors representing these features contain information on played shape as well as a basic representation of tactical dynamics — threats to capture stones, replying to last move, or ignoring opponent's move elsewhere to return to an urgent local situation. The shapes often correspond to opening moves (either in empty corners and sides, or as part of *joseki* — commonly played sequences) characteristic for a certain strategic aim. In the opening, even a single-line difference in the distance from the border can have dramatic impact on further local and global development.

B. Vector Rescaling

The pattern vector elements can have diverse values since for each object, we consider a different number of games (and thus patterns). Therefore, we normalize the values to range $[-1, 1]$, the most frequent pattern having the value of 1 and the least occuring one being -1. Thus, we obtain vectors describing relative frequency of played patterns independent on number of gathered patterns. But there are multiple ways to approach the normalization.

1) Linear Normalization: An intuitive solution is to linearly re-scale the values using:

$$y_i = \frac{x_i - x_{\min}}{x_{\max}}$$

This is the default approach; we have used data processed by only this computation unless we note otherwise. As shown on fig. 1, most of the spectrum is covered by the few most-occuring patterns (describing mostly large-diameter shapes from the game opening). This means that most patterns will be always represented by only very small values near the lower bound.

[1]We do not consider contiguity features in some cases when we are working on small game samples and need to reduce pattern diversity.

[2]The *gridcular* metric $d(x, y) = |\delta x| + |\delta y| + \max(|\delta x|, |\delta y|)$ produces a circle-like structure on the Go board square grid [10].

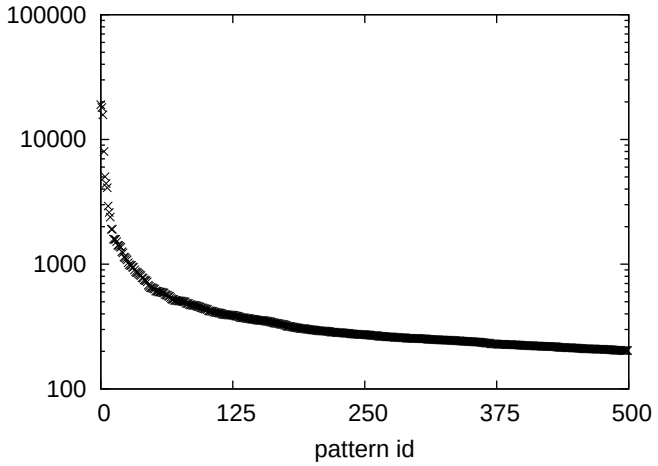


Fig. 1. Log-scaled number of pattern occurences in the GoGoD games examined in sec. V.

2) Extended Normalization: To alleviate this problem, we have also tried to modify the linear normalization by applying two steps — *pre-processing* the raw counts using

$$x'_i = \log(x_i + 1)$$

and *post-processing* the re-scaled values by the logistic function:

$$y'_i = \frac{2}{1 + e^{-cy_i}} - 1$$

However, we have found that this method is not universally beneficial. In our styles case study (sec. V), this normalization produced PCA decomposition with significant dimensions corresponding better to some of the prior knowledge and more instructive for manual inspection, but ultimately worsened accuracy of our classifiers. From this we conjecture that the most frequently occuring patterns are also most important for classification of major style aspects.

C. Implementation

We have implemented the data extraction by making use of the pattern features matching implementation within the Pachi Go-playing program [11], which works according to the Elo-rating pattern selection scheme [9]. We extract information on players by converting the SGF game records to GTP stream [12] that feeds Pachi's `patternscan` engine, producing a single *patternspec* (string representation of the particular pattern features combination) per move. Of course, only moves played by the appropriate player are collected.

III. Data Mining

To assess the properties of gathered pattern vectors and their influence on playing styles, we analyze the data using several basic data minining techniques. The first two methods *(analytic)* rely purely on single data set and serve to show internal structure and correlations within the data set.

Principal Component Analysis (PCA) [13] finds orthogonal vector components that represent the largest variance of values within the dataset. That is, PCA will produce vectors

representing the overall variability within the dataset — the first vector representing the "primary axis" of the dataset, the next vectors representing the less significant axes; each vector has an associated number that determines its impact on the overall dataset variance: 1.0 would mean that all points within the dataset lie on this vector, value close to zero would mean that removing this dimension would have little effect on the overall shape of the dataset.

Reversing the process of the PCA by backprojecting the orthogonal vector components into the original pattern space can indicate which patterns correlate with each component. Additionally, PCA can be used as vector preprocessing for methods that are negatively sensitive to pattern vector component correlations.

On the other hand, Sociomaps [14] [15] [16] produce spatial representation of the data set elements (e.g. players) based on similarity of their data set features. Projecting some other information on this map helps illustrate connections within the data set.

Furthermore, we test several *classification* methods that assign an *output vector* $\vec{O}$ to each pattern vector $\vec{P}$, the output vector representing the information we want to infer from the game sample — e.g. assessment of the playing style, player's strength or even meta-information like the player's era or the country of origin. Initially, the methods must be calibrated (trained) on some prior knowledge, usually in the form of *reference pairs* of pattern vectors and the associated output vectors. The reference set is divided into training and testing pairs and the methods can be compared by the mean square error (MSE) on testing data set (difference of output vectors approximated by the method and their real desired value).

The most trivial method is approximation by the PCA representation matrix, provided that the PCA dimensions have some already well-defined interpretation. This can be true for single-dimensional information like the playing strength. Aside of that, we test the k-Nearest Neighbors (k-*NN*) classifier [17] that approximates $\vec{O}$ by composing the output vectors of k reference pattern vectors closest to $\vec{P}$.

Another classifier is a multi-layer feed-forward Artificial Neural Network (see e.g. [18]). The neural network can learn correlations between input and output vectors and generalize the "knowledge" to unknown vectors. The neural network can be more flexible in the interpretation of different pattern vector elements and discern more complex relations than the k-NN classifier, but may not be as stable and expects larger training sample.

Finally, a commonly used classifier in statistical inference is the Naive Bayes Classifier [19]. It can infer relative probability of membership in various classes based on previous evidence (training patterns).

A. Statistical Methods

We use couple of general statistical analysis methods together with the particular techniques. To find correlations within or between extracted data and some prior knowledge (player rank, style vector), we compute the well-known *Pearson product-moment correlation coefficient (PMCC)* [20], measuring the strength of the linear dependence[3] between any two dimensions:

$$r_{X,Y} = \frac{\operatorname{cov}(X,Y)}{\sigma_X \sigma_Y}$$

To compare classifier performance on the reference data, we employ k-*fold cross validation*: we randomly divide the training set into k distinct segments of similar sizes and then iteratively use each part as a testing set as the other $k-1$ parts are used as a training set. We then average results over all iterations.

B. Principal Component Analysis

We use Principal Component Analysis to reduce the dimensions of the pattern vectors while preserving as much information as possible, assuming inter-dependencies between pattern vector dimensions are linear. Technically, PCA is an eigenvalue decomposition of a covariance matrix of centered pattern vectors, producing a linear mapping o from n-dimensional vector space to a reduced m-dimensional vector space. The m eigenvectors of the original vectors' covariance matrix with the largest eigenvalues are used as the base of the reduced vector space; the eigenvectors form projection matrix W.

For each original pattern vector $\vec{p}_i$, we obtain its new representation $\vec{r}_i$ in the PCA base as shown in the following equation:

$$\vec{r}_i = W \cdot \vec{p}_i \tag{1}$$

The whole process is described in the Algorithm 1.

Algorithm 1 PCA – Principal Component Analysis

Require: $m > 0$, set of players R with pattern vectors p_r
  $\vec{\mu} \leftarrow 1/|R| \cdot \sum_{r \in R} \vec{p}_r$
  for $r \in R$ **do**
    $\vec{p}_r \leftarrow \vec{p}_r - \vec{\mu}$
  end for
  for $(i,j) \in \{1,...,n\} \times \{1,...,n\}$ **do**
    $Cov[i,j] \leftarrow 1/|R| \cdot \sum_{r \in R} \vec{p}_{ri} \cdot \vec{p}_{rj}$
  end for
  Compute Eigenvalue Decomposition of Cov matrix
  Get m largest eigenvalues
  Most significant eigenvectors ordered by decreasing eigenvalues form the rows of matrix W
  for $r \in R$ **do**
    $\vec{r}_r \leftarrow W\vec{p}_r$
  end for

C. Sociomaps

Sociomaps are a general mechanism for visualizing relationships on a 2D plane such that given ordering of the player distances in the dataset is preserved in distances on the plane. In our particular case, we will consider a dataset $\vec{S}$ of small-dimensional vectors $\vec{s}_i$. First, we estimate the *significance* of

[3] A desirable property of PMCC is that it is invariant to translations and rescaling of the vectors.

difference of each two subjects. Then, we determine projection φ of all the $\vec{s}_i$ to spatial coordinates of an Euclidean plane, such that it reflects the estimated difference significances.

To quantify the differences between the subjects (*team profiling*) into an A matrix, for each two subjects i, j we compute the scalar distance[4] of s_i, s_j and then estimate the A_{ij} probability of at least such distance occuring in uniformly-distributed input (the higher the probability, the more significant and therefore important to preserve the difference is).

To visualize the quantified differences, we need to find the φ projection such that it maximizes a *three-way ordering* criterion: ordering of any three members within A and on the plane (by Euclidean metric) must be the same.

$$\max_{\varphi} \sum_{i \neq j \neq k} \Phi(\varphi, i, j, k)$$

$$\Phi(\varphi, i, j, k) = \begin{cases} 1 & \delta(1, A_{ij}, A_{ik}) = \delta(\varphi(i), \varphi(j), \varphi(k)) \\ 0 & \text{otherwise} \end{cases}$$

$$\delta(a, b, c) = \begin{cases} 1 & |a-b| > |a-c| \\ 0 & |a-b| = |a-c| \\ -1 & |a-b| < |a-c| \end{cases}$$

The φ projection is then determined by randomly initializing the position of each subject and then employing gradient descent methods.

D. k-Nearest Neighbors Classifier

Our goal is to approximate the player's output vector $\vec{O}$, knowing their pattern vector $\vec{P}$. We further assume that similarities in players' pattern vectors uniformly correlate with similarities in players' output vectors.

We require a set of reference players R with known *pattern vectors* $\vec{p}_r$ and *output vectors* $\vec{o}_r$. $\vec{O}$ is approximated as weighted average of *output vectors* $\vec{o}_i$ of k players with *pattern vectors* $\vec{p}_i$ closest to $\vec{P}$. This is illustrated in the Algorithm 2. Note that the weight is a function of distance and is not explicitly defined in Algorithm 2. During our research, exponentially decreasing weight has proven to be sufficient, as detailed in each of the case studies.

Algorithm 2 k-Nearest Neighbors

Require: pattern vector $\vec{P}$, $k > 0$, set of reference players R

```
for all r ∈ R do
    D[r] ← EuclideanDistance(p_r, P)
end for
N ← SelectSmallest(k, R, D)
O ← 0
for all r ∈ N do
    O ← O + Weight(D[r]) · o_r
end for
```

[4]We use the *Manhattan* metric $d(x, y) = \sum_i |x_i - y_i|$.

E. Neural Network Classifier

Feed-forward neural networks are known for their ability to generalize and find correlations between input patterns and output classifications. Before use, the network is iteratively trained on the training data until the error on the training set is reasonably small.

1) Computation and activation of the NN: Technically, the neural network is a network of interconnected computational units called neurons. A feed-forward neural network has a layered topology. It usually has one *input layer*, one *output layer* and an arbitrary number of *hidden layers* between. Each neuron i gets input from all neurons in the previous layer, each connection having specific weight w_{ij}.

The computation proceeds in discrete time steps. In the first step, the neurons in the *input layer* are *activated* according to the *input vector*. Then, we iteratively compute output of each neuron in the next layer until the output layer is reached. The activity of output layer is then presented as the result.

The activation y_i of neuron i from the layer I is computed as

$$y_i = f\left(\sum_{j \in J} w_{ij} y_j\right) \tag{2}$$

where J is the previous layer, while y_j is the activation for neurons from J layer. Function $f()$ is a so-called *activation function* and its purpose is to bound the outputs of neurons. A typical example of an activation function is the sigmoid function.[5]

2) Training: Training of the feed-forward neural network usually involves some modification of supervised Backpropagation learning algorithm. We use first-order optimization algorithm called RPROP [21]. As outlined above, the training set T consists of $(\vec{p}_i, \vec{o}_i)$ pairs. The training algorithm is shown in Algorithm 3.

Algorithm 3 Training Neural Network

Require: Train set T, desired error e, max iterations M

```
N ← RandomlyInitializedNetwork()
It ← 0
repeat
    It ← It + 1
    ΔW ← 0
    TotalError ← 0
    for all (Input, DesiredOutput) ∈ T do
        Output ← Result(N, Input)
        Error ← |DesiredOutput − Output|
        ΔW ← ΔW + WeightUpdate(N, Error)
        TotalError ← TotalError + Error
    end for
    N ← ModifyWeights(N, ΔW)
until TotalError < e or It > M
```

[5]A special case of the logistic function $\sigma(x) = (1 + e^{-(rx+k)})^{-1}$. Parameters control the growth rate r and the x-position k.

F. Naive Bayes Classifier

The Naive Bayes Classifier uses existing information to construct probability model of likelihoods of given *feature variables* based on a discrete-valued *class variable*. Using the Bayes equation, we can then estimate the probability distribution of class variable for particular values of the feature variables.

In order to approximate the player's output vector $\vec{O}$ based on pattern vector $\vec{P}$, we will compute each element of the output vector separately, covering the output domain by several k-sized discrete intervals (classes). In fact, we use the PCA-represented input $\vec{R}$ (using the 10 most significant dimensions), since it better fits the pre-requisites of the Bayes classifier – values in each dimension are more independent and they approximate the normal distribution better. Additionally, small input dimensions are computationaly feasible.

When training the classifier for $\vec{O}$ element o_i of class $c = \lfloor o_i/k \rfloor$, we assume the $\vec{R}$ elements are normally distributed and feed the classifier information in the form

$$\vec{R} \mid c$$

estimating the mean μ_c and standard deviation σ_c of each $\vec{R}$ element for each encountered c (see algorithm 4). Then, we can query the built probability model on

$$\max_c P(c \mid \vec{R})$$

obtaining the most probable class i for an arbitrary $\vec{R}$ Each probability is obtained using the normal distribution formula:

$$P(c \mid x) = \frac{1}{\sqrt{2\pi\sigma_c^2}} \exp \frac{-(x-\mu_c)^2}{2\sigma_c^2}$$

Algorithm 4 Training Naive Bayes

Require: Training set $T = (R, c)$
  for all $(R, c) \in T$ **do**
    $RbyC_c \leftarrow RbyC_c \cup \{R\}$
  end for
  for all c **do**
    $\mu_c \leftarrow \frac{1}{|RbyC_c|} \sum_{R \in RbyC_c} R$
  end for
  for all c **do**
    $\sigma_c \leftarrow \frac{1}{|RbyC_c|} \sum_{R \in RbyC_c} R - \mu_c$
  end for

G. Implementation

We have implemented the data mining methods as the "gostyle" open-source framework [22], made available under the GNU GPL licence. The majority of our basic processing and analysis is implemented in the Python [23] programming language.

We use several external libraries, most notably the MDP library [24] for the PCA analysis. The neural network component is written using the libfann C library [25]. The Naive Bayes Classifier is built around the `AI::NaiveBayes1` Perl module [26]. The sociomap has been visualised using the Team Profile Analyzer [27] which is a part of the Sociomap suite [28].

IV. Strength Analysis

First, we have used our framework to analyse correlations of pattern vectors and playing strength. Like in other competitively played board games, Go players receive real-world *rating number* based on tournament games, and *rank* based on their rating. The amateur ranks range from 30-kyu (beginner) to 1-kyu (intermediate) and then follows 1-dan to 9-dan (top-level player).

There are multiple independent real-world ranking scales (geographically based), while online servers also maintain their own user rank list. The difference between scales can be up to several ranks and the rank distributions also differ [29].

A. Data source

As the source game collection, we use the Go Teaching Ladder reviews archive [30]. This collection contains 7700 games of players with strength ranging from 30-kyu to 4-dan; we consider only even games with clear rank information.

Since the rank information is provided by the users and may not be consistent, we are forced to take a simplified look at the ranks, discarding the differences between various systems and thus somewhat increasing error in our model.[6] We represent the rank in our dataset as an integer in the range $[-3, 30]$ with positive numbers representing the kyu ranks and numbers smaller than 1 representing the dan ranks: 4-dan maps to -3, 1-dan to 0, etc.

B. Strength PCA analysis

First, we have created a single pattern vector for each rank between 30-kyu to 4-dan; we have performed PCA analysis on the pattern vectors, achieving near-perfect rank correspondence in the first PCA dimension[7] (figure 2). We measure the accuracy of the strength approximation by the first PCA dimension using Pearson's r (see III-A), yielding very satisfying value of $r = 0.979$ implying extremely strong correlation.

This reflects the trivial fact that the most important "defining characteristic" of a set of players grouped by strength is indeed their strength and confirms that our methodics is correct. At the same time, this result suggests that it is possible to accurately estimate player's strength just from a sample of his games, as we confirm below.

When investigating a player's $\vec{p}$, the PCA decomposition could be also useful for study suggestions — a program could examine the pattern gradient at the player's position on the PCA dimensions and suggest patterns to avoid and patterns to play more often. Of course, such an advice alone is certainly not enough and it must be used only as a basis of a more thorough analysis of reasons behind the fact that the player plays other patterns than they "should".

[6] Since our results seem satisfying, we did not pursue to try another collection; one could e.g. look at game archives of some Go server to work within single more-or-less consistent rank model.

[7] The eigenvalue of the second dimension was four times smaller, with no discernable structure revealed within the lower-order eigenvectors.

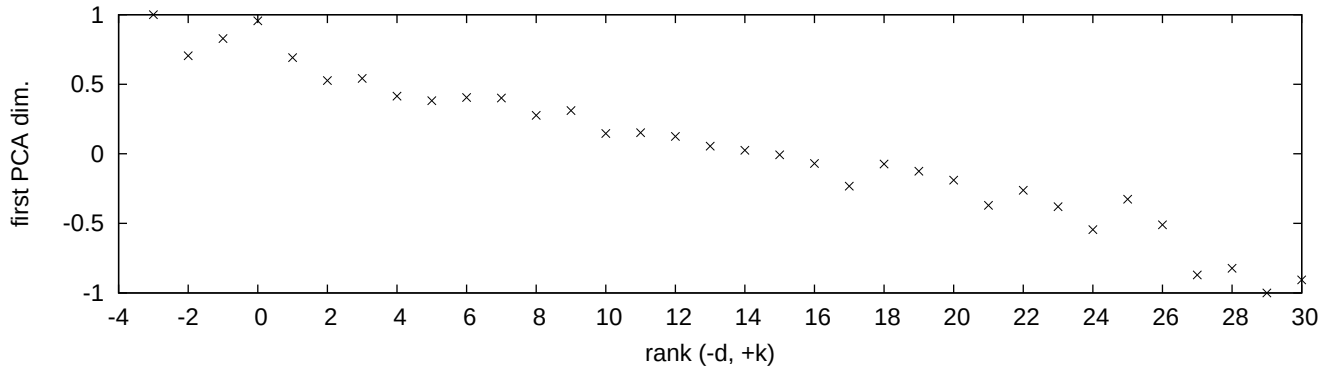


Fig. 2. PCA of by-strength vectors

C. Strength Classification

In line with results of the PCA analysis, we have tested the strength approximation ability of k-NN (sec. III-D), neural network (sec. III-E), and a simple PCA-based classifier (sec. III-B).

1) Reference (Training) Data: We have trained the tested classifiers using one pattern vector per rank (aggregate over all games played by some player declaring the given rank), then performing PCA analysis to reduce the dimension of pattern vectors. We have explored the influence of different game sample sizes (G) on the classification accuracy to determine the practicality and scaling abilities of the classifiers. In order to reduce the diversity of patterns (negatively impacting accuracy on small samples), we do not consider the contiguity pattern features.

The classifiers were compared by running a many-fold validation by repeatedly and exhaustively taking disjunct G–game samples of the same rank from the collection and measuring the standard error of the classifier. Arbitrary game numbers were approximated by pattern file sizes, iteratively selecting all games of randomly selected player of the required strength.

2) Results: The results are shown in the table I. The G column describes the number of games in each sample, MSE column shows measured mean square error and σ is the empirical standard deviation. Methods are compared (column Cmp) to the random classifier by the quotient of their σ.

From the table, it should be obvious that the k-NN is obtaining good accuracy even on as few as 9 games as a sample, where the classifier performs within a standard deviation of 4.6kyu. For a large number of training vectors – albeit not very accurate due to small sample sizes – the neural network classifier performs very similarly. For samples of 2 games, the neural network is even slightly better on average. However, due to the decreasing number of training vectors with increasing game sample sizes, the neural network gets unusable for large game sample sizes. The table therefore only shows the neural network results for samples of 17 games and smaller. PCA-based classifier (the most significant PCA eigenvector position is simply directly taken as a rank) and a random classifier are listed mainly for the sake of comparison, because they do not perform competetively.

TABLE I
STRENGTH CLASSIFIER PERFORMANCE

Method	G	MSE	σ	Cmp
k-NN	85	5.514	2.348	6.150
	43	8.449	2.907	4.968
	17	10.096	3.177	4.545
	9	21.343	4.620	3.126
	2	52.212	7.226	1.998
Neural Network	17	110.633	10.518	1.373
	9	44.512	6.672	2.164
	2	43.682	6.609	2.185
PCA	85	24.070	4.906	2.944
	43	31.324	5.597	2.580
	17	50.390	7.099	2.034
	9	72.528	8.516	1.696
	2	128.660	11.343	1.273
Rnd	N/A	208.549	14.441	1.000

3) k-NN parameters: Using the 4-Nearest Neighbors classifier with the weight function

$$Weight(\vec{x}) = 0.9^{M*Distance(\vec{x})} \tag{3}$$

(parameter M ranging from 30 to 6).

4) Neural network's parameters: The neural network classifier had three-layered architecture (one hidden layer) comprising of these numbers of neurons:

Layer		
Input	Hidden	Output
119	35	1

The network was trained until the square error on the training set was smaller than 0.0005. Due to the small number of input vectors, this only took about 20 iterations of RPROP learning algorithm on average.

V. STYLE ANALYSIS

As a second case study for our pattern analysis, we investigate pattern vectors $\vec{p}$ of various well-known players, their relationships in-between and to prior knowledge in order

TABLE II
COVARIANCE MEASURE OF PRIOR INFORMATION DIMENSIONS

	τ	ω	α	θ	year
τ	1.000	$\mathbf{-0.438}$	$\mathbf{-0.581}$	$\mathbf{0.721}$	0.108
ω		1.000	$\mathbf{0.682}$	0.014	-0.021
α			1.000	-0.081	0.030
θ		—		1.000	-0.073
y.					1.000

to explore the correlation of prior knowledge with extracted patterns. We look for relationships between pattern vectors and perceived "playing style" and attempt to use our classifiers to transform the pattern vector $\vec{p}$ to a style vector $\vec{s}$.

A. Data sources

1) Game database: The source game collection is GoGoD Winter 2008 [31] containing 55000 professional games, dating from the early Go history 1500 years ago to the present. We consider only games of a small subset of players (table III). These players were chosen for being well-known within the players community, having large number of played games in our collection and not playing too long ago.

2) Expert-based knowledge: In order to provide a reference frame for our style analysis, we have gathered some information from game experts about various traditionally perceived style aspects to use as a prior knowledge. This expert-based knowledge allows us to predict styles of unknown players based on the similarity of their pattern vectors, as well as discover correlations between styles and particular move patterns.

Experts were asked to mark four style aspects of each of the given players on the scale from 1 to 10. The style aspects are defined as shown:

Style	1	10
Territoriality τ	Moyo	Territory
Orthodoxity ω	Classic	Novel
Aggressivity α	Calm	Fighting
Thickness θ	Safe	Shinogi

We have devised these four style aspects based on our own Go experience and consultations with other experts. The used terminology has quite clear meaning to any experienced Go player and there is not too much room for confusion, except possibly in the case of "thickness" — but the concept is not easy to pin-point succintly and we also did not add extra comments on the style aspects to the questionnaire deliberately to accurately reflect any diversity in understanding of the terms. Averaging this expert based evaluation yields *reference style vector* $\vec{s}_r$ (of dimension 4) for each player r from the set of *reference players* R.

Throughout our research, we have experimentally found that playing era is also a major factor differentiating between patterns. Thus, we have further extended the $\vec{s}_r$ by median year over all games played by the player.

Three high-level Go players (Alexander Dinerstein 3-pro, Motoki Noguchi 7-dan and Vít Brunner 4-dan) have judged the style of the reference players. The complete list of answers is in table III. Standard error of the answers is 0.952, making the data reasonably reliable, though much larger sample would of course be more desirable (but beyond our means to collect). We have also found a significant correlation between the various style aspects, as shown by the Pearson's r values in table II.

We have made few manual adjustments in the dataset, disregarding some players or portions of their games. This was done to achieve better consistency of the games (e.g. considering only games of roughly the same age) and to consider only sets of games that can be reasonably rated as a whole by human experts (who can give a clear feedback in this effect). This filtering methodology can be easily reproduced and such arbitrary decisions are neccessary only for processing the training dataset, not for using it (either for exloration or classification).

B. Style PCA analysis

We have looked at the ten most significant dimensions of the pattern data yielded by the PCA analysis of the reference player set (fig. 3 shows the first three). We have again computed the Pearson's r for all combinations of PCA dimensions and dimensions of the prior knowledge style vectors to find correlations.

It is immediately obvious both from the measured r and visual observation that by far the most significant vector corresponds very well to the territoriality of the players, confirming the intuitive notion that this aspect of style is the one easiest to pin-point and also most obvious in the played shapes and sequences (that can obviously aim directly at taking secure territory or building center-oriented framework). Thick (solid) play also plays a role, but these two style dimensions are already correlated in the prior data.

The other PCA dimensions are somewhat harder to interpret, but there certainly is significant influence of the styles on the patterns; the correlations are all presented in table IV. (Larger absolute value means better linear correspondence.)

We also list the characteristic spatial patterns of the PCA dimension extremes (tables V, VI), determined by their coefficients in the PCA projection matrix — however, such naive approach has limited reliability, better methods will have to be researched.[8] We do not show the other pattern features since they carry no useful information in the opening stage.

The PCA results presented above do not show much correlation between the significant PCA dimensions and the ω and α style dimensions. However, when we applied the extended vector normalization (sec. II-B2; see table VII), some less significant PCA dimensions exhibited clear correlations.[9] While we do not use the extended normalization results elsewhere

[8]For example, as one of highly ranked "Takemiya's" PCA1 patterns, 3,3 corner opening was generated, completely inappropriately; it reflects some weak ordering in bottom half of the dimension, not global ordering within the dimension.

[9]We have found that $c = 6$ in the post-processing logistic function produces the most instructive PCA output on our particular game collection.

TABLE III
EXPERT-BASED STYLE ASPECTS OF SELECTED PROFESSIONALS[1] [2]

Player	τ	ω	α	θ
Go Seigen[3]	6.0 ± 2.0	9.0 ± 1.0	8.0 ± 1.0	5.0 ± 1.0
Ishida Yoshio[4]	8.0 ± 1.4	5.0 ± 1.4	3.3 ± 1.2	5.3 ± 0.5
Miyazawa Goro	1.5 ± 0.5	10 ± 0	9.5 ± 0.5	4.0 ± 1.0
Yi Ch'ang-ho[5]	7.0 ± 0.8	5.0 ± 1.4	2.6 ± 0.9	2.6 ± 1.2
Sakata Eio	7.6 ± 1.7	4.6 ± 0.5	7.3 ± 0.9	8.0 ± 1.6
Fujisawa Hideyuki	3.5 ± 0.5	9.0 ± 1.0	7.0 ± 0.0	4.0 ± 0.0
Otake Hideo	4.3 ± 0.5	3.0 ± 0.0	4.6 ± 1.2	3.6 ± 0.9
Kato Masao	2.5 ± 0.5	4.5 ± 1.5	9.5 ± 0.5	4.0 ± 0.0
Takemiya Masaki[4]	1.3 ± 0.5	6.3 ± 2.1	7.0 ± 0.8	1.3 ± 0.5
Kobayashi Koichi	9.0 ± 1.0	2.5 ± 0.5	2.5 ± 0.5	5.5 ± 0.5
Cho Chikun	9.0 ± 0.8	7.6 ± 0.9	6.6 ± 1.2	9.0 ± 0.8
Ma Xiaochun	8.0 ± 2.2	6.3 ± 0.5	5.6 ± 1.9	8.0 ± 0.8
Yoda Norimoto	6.3 ± 1.7	4.3 ± 2.1	4.3 ± 2.1	3.3 ± 1.2
Luo Xihe	7.3 ± 0.9	7.3 ± 2.5	7.6 ± 0.9	6.0 ± 1.4
O Meien	2.6 ± 1.2	9.6 ± 0.5	8.3 ± 1.7	3.6 ± 1.2
Rui Naiwei	4.6 ± 1.2	5.6 ± 0.5	9.0 ± 0.8	3.3 ± 1.2
Yuki Satoshi	3.0 ± 1.0	8.5 ± 0.5	9.0 ± 1.0	4.5 ± 0.5
Hane Naoki	7.5 ± 0.5	2.5 ± 0.5	4.0 ± 0.0	4.5 ± 1.5
Takao Shinji	5.0 ± 1.0	3.5 ± 0.5	5.5 ± 1.5	4.5 ± 0.5
Yi Se-tol	5.3 ± 0.5	6.6 ± 2.5	9.3 ± 0.5	6.6 ± 1.2
Yamashita Keigo[4]	2.0 ± 0.0	9.0 ± 1.0	9.5 ± 0.5	3.0 ± 1.0
Cho U	7.3 ± 2.4	6.0 ± 0.8	5.3 ± 1.7	6.3 ± 1.7
Gu Li	5.6 ± 0.9	7.0 ± 0.8	9.0 ± 0.8	4.0 ± 0.8
Chen Yaoye	6.0 ± 1.0	4.0 ± 1.0	6.0 ± 1.0	5.5 ± 0.5

[1] Including standard deviation. Only players where we received at least two out of three answers are included.
[2] Since the playing era column does not fit into the table, we at least sort the players ascending by their median year.
[3] We do not consider games of Go Seigen due to him playing across several distinct eras and also being famous for radical opening experiments throughout the time, and thus featuring especially high diversity in patterns.
[4] We do not consider games of Ishida Yoshio and Yamashita Keigo for the PCA analysis since they are significant outliers, making high-order dimensions much like purely "similarity to this player". Takemiya Masaki has the similar effect for the first dimension, but that case corresponds to common knowledge of him being an extreme proponent of anti-territorial ("moyo") style.
[5] We consider games only up to year 2004, since Yi Ch'ang-ho was prominent representative of a balanced, careful player until then and still has this reputation in minds of many players, but is regarded to have altered his style significantly afterwards.

TABLE IV
COVARIANCE MEASURE OF PCA AND PRIOR INFORMATION

Eigenval.	τ	ω	α	θ	Year
0.447	$\mathbf{-0.530}$	0.323	0.298	$\mathbf{-0.554}$	0.090
0.194	$\mathbf{-0.547}$	0.215	0.249	-0.293	$\mathbf{-0.630}$
0.046	0.131	-0.002	-0.128	0.242	$\mathbf{-0.630}$
0.028	-0.011	0.225	0.186	0.131	0.067
0.024	-0.181	0.174	-0.032	-0.216	0.352

since they produced noticeably less accurate classifiers in all dimensions (including ω and α), it is instructive to look at the PCA dimensions.

In contrast with the emphasis of opening patterns in the τ and θ dimensions, the most contributing patterns of the ω and

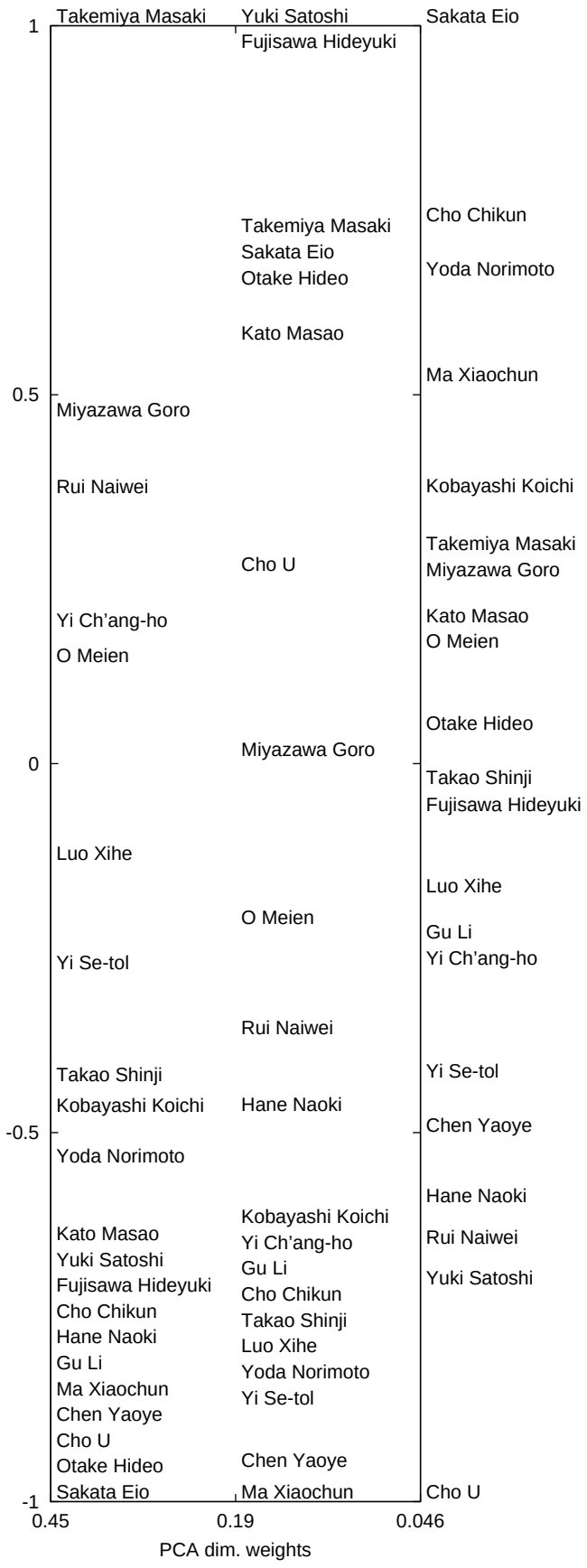
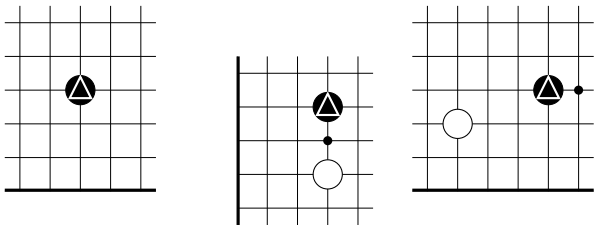


Fig. 3. Columns with the most significant PCA dimensions of the dataset.

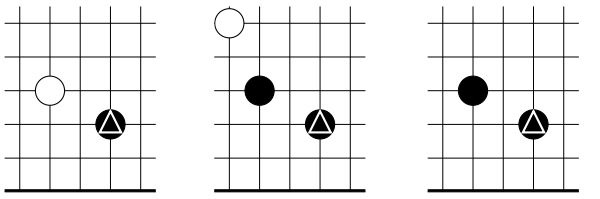
TABLE V
CHARACTERISTIC PATTERNS OF $PCA_{1,2}$ DIMENSIONS [1]

PCA_1 — Moyo-oriented, thin-playing player



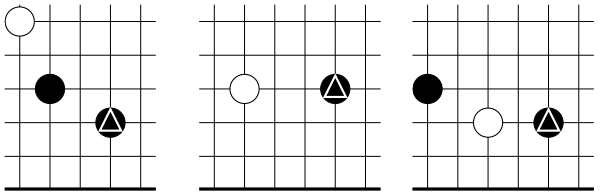
0.274	0.086	0.083
high corner/side opening [2]	high corner approach	high distant pincer

PCA_1 — Territorial, thick-playing player



−0.399	−0.399	−0.177
low corner approach	low corner reply	low corner enclosure

PCA_2 — Territorial, current player [3]

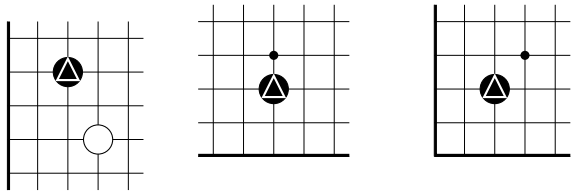


−0.193	−0.139	−0.135
low corner reply [4]	high distant approach/pincer	near low pincer

[1] We present the patterns in a simplified compact form; in reality, they are usually somewhat larger and always circle-shaped (centered on the triangled move). We omit only pattern segments that are entirely empty.
[2] We give some textual interpretation of the patterns, especially since some of them may not be obvious unless seen in game context; we choose the descriptions based on the most frequently observer contexts, but of course the pattern can be also matched in other positions and situations.
[3] In the second PCA dimension, we find no correlated patterns; only uncorrelated and anti-correlated ones.
[4] As the second most significant pattern, we skip a slide follow-up pattern to this move.

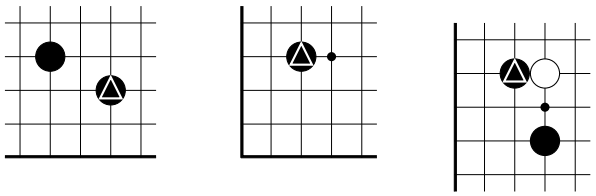
TABLE VI
CHARACTERISTIC PATTERNS OF PCA_3 DIMENSION [1]

PCA_3 — Old-time player



0.515	0.264	0.258
low corner approach	low side or mokuhazushi opening	san-san opening

PCA_3 — Current player



−0.276	−0.273	−0.116
low corner enclosure	3-4 corner opening [2]	high approach reply

[1] We cannot use terms “classic” and ”modern” in case of PCA_3 since the current patterns are commonplace in games of past centuries (not included in our training set) and many would call a lot of the old-time patterns modern inventions. Perhaps we can infer that the latest 21th-century play trends abandon many of the 20th-century experiments (lower echelon of our by-year samples) to return to the more ordinary but effective classic patterns.
[2] At this point, we skip two patterns already shown elsewhere: *high side/corner opening* and *low corner reply*.

TABLE VII
COVARIANCE MEASURE OF EXTERNED-NORMALIZATION PCA AND PRIOR INFORMATION

Eigenval.	τ	ω	α	θ	Year
6.377	**0.436**	−0.220	−0.289	**0.404**	**−0.576**
1.727	**−0.690**	0.340	0.315	**−0.445**	**−0.639**
1.175	−0.185	0.156	0.107	−0.315	0.320
0.845	0.064	−0.102	−0.189	0.032	0.182
0.804	−0.185	0.261	**0.620**	0.120	0.056
0.668	−0.027	0.055	0.147	−0.198	0.155
0.579	0.079	**0.509**	0.167	0.294	−0.019

α dimensions are the middle-game patterns that occur less frequently and require the extended normalization not to be over-shadowed by the opening patterns.[10] E.g. the most characteristic patterns on the aggressiveness dimension represent moves that make life with small, unstable groups (connecting kosumi on second line or mouth-shape eyespace move), while the novel-ranked players seem to like the (in)famous tsuke-nobi joseki sequence.[11] This may either mean that novel players like to play the joseki more, or (more likely, in our opinion) that novel players are more likely to get into unorthodox situation that require resorting to the tsuke-nobi sequence. We believe that the next step in interpreting our analytical results will be more refined prior information input and precise analysis of the outputs by Go experts.

Fig. 4 shows the Sociomap visualisation as an alternate view of the player relationships and similarity, as well as correlation between the expert-given style marks and the PCA decomposition. The four-dimensional style vectors are used

[10] In the middle game, basic areas of influence have been staked out and invasions and group attacks are being played out. Notably, the board is much more filled than in the opening and thus particular specific-shape patterns repeat less often.

[11] Tsuke-nobi is a well-known joseki popular among beginners, but professionals usually play it only in special contexts.

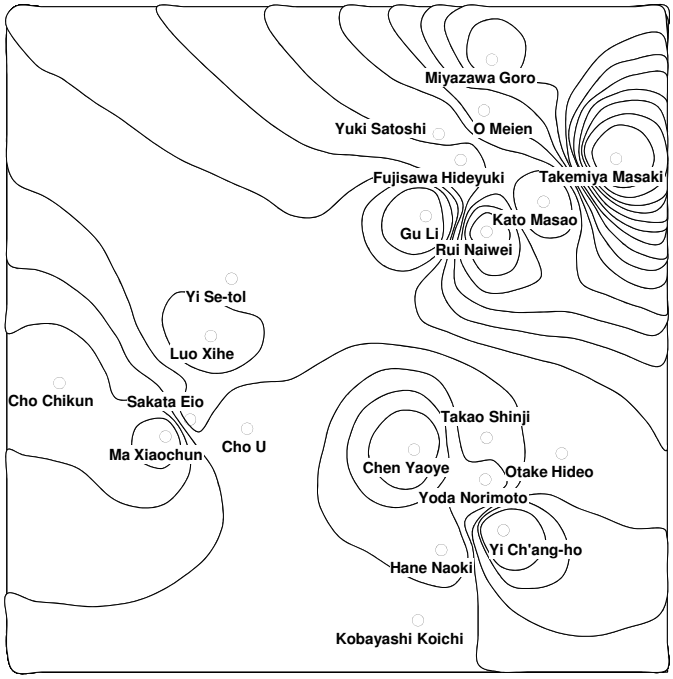


Fig. 4. Sociomap visualisation. The spatial positioning of players is based on the expert knowledge, while the node heights (depicted by contour lines) represent the pattern vectors.

as input for the Sociomap renderer and determine the spatial positions of players. The height of a node is then determined using first two PCA dimensions R_1, R_2 and their eigenvalues λ_1, λ_2 as their linear combination:

$$h = \lambda_1 R_1 + \lambda_2 R_2$$

We can observe that the terrain of the sociomap is reasonably "smooth", again demonstrating some level of connection between the style vectors and data-mined information. High countour density indicates some discrepancy; in case of Takemiya Masaki and Yi Ch'ang-ho, this seems to be merely an issue of scale, while the Rui Naiwei — Gu Li cliff suggests a genuine problem; we cannot say now whether it is because of imprecise prior information or lacking approximation abilities of our model.

C. Style Classification

Similarly to the the Strength classification (section IV-C), we have tested the style inference ability of k-NN (sec. III-D), neural network (sec. III-E), and Bayes (sec. III-F) classifers.

1) Reference (Training) Data: As the reference data, we use expert-based knowledge presented in section V-A2. For each reference player, that gives 4-dimensional *style vector* (each component in the range of $[1, 10]$).[12]

All input (pattern) vectors were preprocessed using PCA, reducing the input dimension from 400 to 23. We measure the performance on the same reference data using 5-fold cross validation. To put our measurements in scale, we also include a random classifier in our results.

[12]Since the neural network has activation function with range $[-1, 1]$, we have linearly rescaled the *style vectors* from interval $[1, 10]$ to $[-1, 1]$ before using the training data. The network's output was afterwards rescaled back to allow for MSE comparison.

TABLE VIII
COMPARISON OF STYLE CLASSIFIERS

	MSE					
Classifier	τ	ω	α	θ	**Mean**	**Cmp**
Joint classifier[1]	4.04	**5.25**	**3.52**	**3.05**	**3.960**	2.97
Neural network	**4.03**	6.15	**3.58**	3.79	4.388	2.68
k-NN ($k = 2$)	4.08	5.40	4.77	3.37	4.405	2.67
k-NN ($k = 3$)	4.05	5.58	5.06	3.41	4.524	2.60
k-NN ($k = 1$)	4.52	**5.26**	5.36	**3.09**	4.553	2.59
k-NN ($k = 4$)	4.10	5.88	5.16	3.60	4.684	2.51
Naive Bayes	4.48	6.90	5.48	3.70	5.143	2.29
Random class.	12.26	12.33	12.40	10.11	11.776	1.00

[1] Note that these measurements have a certain variance. Since the Joint classifier performance was measured from scratch, the precise values may not match appropriate cells of the used methods.

2) Results: The results are shown in the table VIII. Second to fifth columns in the table represent mean square error (MSE) of the examined styles, $Mean$ is the mean square error across the styles and finally, the last column Cmp represents $Mean(Randomclassifier)/Mean(X)$ – comparison of mean square error of each method with the random classifier. To minimize the effect of random variables, all numbers were taken as an average of 200 runs of the cross validation.

Analysis of the performance of k-NN classifier for different k-values has shown that different k-values are suitable to approximate different styles. Combining the k-NN classifiers with the neural network (so that each style is approximated by the method with lowest MSE in that style) results in *Joint classifier*, which outperforms all other methods. The *Joint classifier* has outstanding MSE 3.960, which is equivalent to standard error of $\sigma = 1.99$ per style.[13]

3) k-NN parameters: All three variants of k-NN classifier ($k = 2, 3, 4$) had the weight function

$$Weight(\vec{x}) = 0.8^{10 * Distance(\vec{x})} \tag{4}$$

The parameters were chosen empirically to minimize the MSE.

4) Neural network's parameters: The neural network classifier had three-layered architecture (one hidden layer) comprising of these numbers of neurons:

Layer		
Input	Hidden	Output
23	30	4

The network was trained until the square error on the training set was smaller than 0.0003. Due to a small number of input vectors, this only took 20 iterations of RPROP learning algorithm on average.

5) Naive Bayes parameters: We have chosen $k = 10/7$ as our discretization parameter; ideally, we would use $k = 1$ to fully cover the style marks domain, however our training sample turns out to be too small for that.

[13]We should note that the pattern vector for each tested player was generated over at least few tens of games.

VI. Proposed Applications

We believe that our findings might be useful for many applications in the area of Go support software as well as Go-playing computer engines. However, our foremost aim is to use the style analysis as an excellent teaching aid — classifying style dimensions based on player's pattern vector, many study recommendations can be given, e.g. about the professional games to replay, the goal being balancing understanding of various styles to achieve well-rounded skill set.[14] A user-friendly tool based on our work is currently in development.

Another promising application we envision is helping to determine the initial real-world rating of a player before their first tournament based on a sample of their games played on the internet; some players especially in less populated areas could get fairly strong before playing in their first real tournament. Similarly, a computer Go program can quickly classify the level of its human opponent based on the pattern vector from their previous games and auto-adjust its difficulty settings accordingly to provide more even games for beginners. This can also be achieved using win-loss statistics, but pattern vector analysis should converge faster initially, providing a much better user experience.

We hope that more strong players will look into the style dimensions found by our statistical analysis — analysis of most played patterns of prospective opponents might prepare for a tournament game, but we especially hope that new insights on strategic purposes of various shapes and general human understanding of the game might be improved by investigating the style-specific patterns.

Of course, it is challenging to predict all possible uses of our work by others. Some less obvious applications might include analysis of pattern vectors extracted from games of Go-playing programs: the strength and style classification might help to highlight some weaknesses and room for improvements.[15] Also, new historical game records are still occassionally being discovered; pattern-based classification might help to suggest or verify origin of the games in Go Archeology.

VII. Future Research

Since we are not aware of any previous research on this topic and we are limited by space and time constraints, plenty of research remains to be done in all parts of our analysis — we have already noted many in the text above. Most significantly, different methods of generating and normalizing the $\vec{p}$ vectors can be explored and other data mining methods could be investigated. Better ways of visualising the relationships would be desirable, together with thorough expert dissemination of internal structure of the player pattern vectors space: more professional players should be consulted on the findings and for style scales calibration.

[14]The strength analysis could be also used in a similar fashion, but the lesson learned cannot simply be "play pattern X more often"; instead, the insight lays in the underlying reason of disproportionate frequency of some patterns.

[15]Of course, correlation does not imply causation and we certainly do not suggest simply optimizing Go-playing programs according to these vectors. However, they could hint on general shortcomings of the playing engines if the actual cause of e.g. surprisingly low strength prediction is investigated.

It can be argued that many players adjust their style by game conditions (Go development era, handicap, komi and color, time limits, opponent) or that styles might express differently in various game stages. These factors should be explored by building pattern vectors more carefully than by simply considering all moves in all games of a player. Impact of handicap and uneven games on by-strength $\vec{p}$ distribution should be also investigated.

VIII. Conclusion

We have proposed a way to extract summary pattern information from game collections and combined this with various data mining methods to show correspondence of our pattern summaries with various player meta-information such as playing strength, era of play or playing style, as ranked by expert players. We have implemented and measured our proposals in two case studies: per-rank characteristics of amateur players and per-player style/era characteristics of well-known professionals.

While many details remain to be worked out, we have demonstrated that many significant correlations doubtlessly do exist and it is practically viable to infer the player meta-information from extracted pattern summaries and we have proposed applications for such inference. Finally, we outlined some of the many possible directions of future work in this newly staked research field on the boundary of Computer Go, Data Mining and Go Theory.

Acknowledgment

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References

[1] S. Gelly and D. Silver, "Achieving master level play in 9x9 computer go," in *AAAI'08: Proceedings of the 23rd national conference on Artificial intelligence*. AAAI Press, 2008, pp. 1537–1540.

[2] Kazuhiro. (2010) KGS Analytics. [Online]. Available: http://kgs.gosquares.net/

[3] A. Cieply *et al.* (2008) Go Ratings of Professional and Strong Amateur Players. [Online]. Available: http://www.goweb.cz/progor

[4] U. Görtz. (2012) Kombilo — a Go database program (version 0.7). [Online]. Available: http://www.u-go.net/kombilo/

[5] F. de Groot. (2005) Moyo Go Studio. [Online]. Available: http://www.moyogo.com/

[6] D. Bump, G. Farneback, A. Bayer *et al.* (2009) GNU Go. [Online]. Available: http://www.gnu.org/software/gnugo/

[7] A. Ghoneim, D. Essam, and H. Abbass, "Competency awareness in strategic decision making," in *Cognitive Methods in Situation Awareness and Decision Support (CogSIMA), 2011 IEEE First International Multi-Disciplinary Conference on*, feb. 2011, pp. 106 –109.

[8] A. Hollosi. (2006) SGF File Format. [Online]. Available: http://www.red-bean.com/sgf/

[9] R. Coulom, "Computing Elo Ratings of Move Patterns in the Game of Go," in *Computer Games Workshop*, H. J. van den Herik, Mark Winands, Jos Uiterwijk, and Maarten Schadd, Eds., Amsterdam Pays-Bas, 2007. [Online]. Available: http://hal.inria.fr/inria-00149859/en/

[10] D. Stern, R. Herbrich, and T. Graepel, “Bayesian pattern ranking for move prediction in the game of go,” in *ICML ’06: Proceedings of the 23rd international conference on Machine learning*. New York, NY, USA: ACM, 2006, pp. 873–880.
[11] P. Baudiš *et al.* (2012) Pachi — Simple Go/Baduk/Weiqi Bot. [Online]. Available: http://repo.or.cz/w/pachi.git
[12] G. Farnebäck. (2001) Gtp — Go Text Protocol (version 1). [Online]. Available: http://www.lysator.liu.se/∼gunnar/gtp/
[13] I. Jolliffe, *Principal Component Analysis*. Springer, New York, 1986.
[14] C. Höschl, *Visualization of Sociomaps*. Bachelor Thesis, MFF UK, 2006.
[15] T. Srb, J. Sýkora, R. Bahbouh, and C. Höschl, “Using visualisation of group structure and dynamics in team development,” in *50thConference of theInternational Military Training Association*, 2008.
[16] C. Höschl, personal communication, 2010.
[17] T. M. Cover and P. E. Hart, “Nearest neighbor pattern classification,” *IEEE Transactions on Information Theory*, vol. 13, no. 1, pp. 21–27, 1967.
[18] S. Haykin, *Neural Networks: A Comprehensive Foundation*. New York: Macmillan, 1994.
[19] R. O. Duda and P. E. Hart, *Pattern classification and scene analysis*. A Wiley-Interscience Publication, New York: Wiley, 1973.
[20] J. L. Rodgers and W. A. Nicewander, “Thirteen ways to look at the correlation coefficient,” *The American Statistician*, vol. 42, no. 1, pp. 59–66, Feb 1988.
[21] M. Riedmiller and H. Braun, “A Direct Adaptive Method for Faster Backpropagation Learning: The RPROP Algorithm,” in *IEEE International Conference on Neural Networks*, 1993, pp. 586–591.
[22] J. Moudřík and P. Baudiš. (2011) GoStyle — Determine playing style in the game of Go. [Online]. Available: http://repo.or.cz/w/gostyle.git
[23] Python Software Foundation. (2006, September) Python 2.5. [Online]. Available: http://www.python.org/dev/peps/pep-0356/
[24] Z. Tiziano, W. Niko, W. Laurenz, and B. Pietro, “Modular toolkit for Data Processing (MDP): a Python data processing framework,” *Frontiers in Neuroinformatics*, vol. 2, 2008.
[25] S. Nissen, “Implementation of a fast artificial neural network library (fann),” Department of Computer Science University of Copenhagen (DIKU), Tech. Rep., 2003, http://fann.sf.net.
[26] V. Keselj, Y.-c. Lin *et al.* (2011) AI::NaiveBayes1 CPAN Module. [Online]. Available: http://search.cpan.org/∼vlado/AI-NaiveBayes1-2.006/NaiveBayes1.pm
[27] QED GROUP. (2012) Team Profile Analyzer. [Online]. Available: http://www.teamprofileanalyzer.com/
[28] ——. (2012) Sociomapping Suite. [Online]. Available: http://www.sociomap.com/
[29] Sensei’s Library. (2012, March) Rank — worldwide comparison. [Online]. Available: http://senseis.xmp.net/?RankWorldwideComparison
[30] J. loup Gailly, B. Hosken *et al.* (2011) The Go Teaching Ladder. [Online]. Available: http://gtl.xmp.net/
[31] T. M. Hall and J. Fairbairn. (winter 2008) Games of Go on Disk — GoGoD Encyclopaedia and Database. [Online]. Available: http://www.gogod.co.uk/
[32] GoDiscussions. Pro Styles (discussion thread). [Online]. Available: http://www.godiscussions.com/forum/showthread.php?t=10980