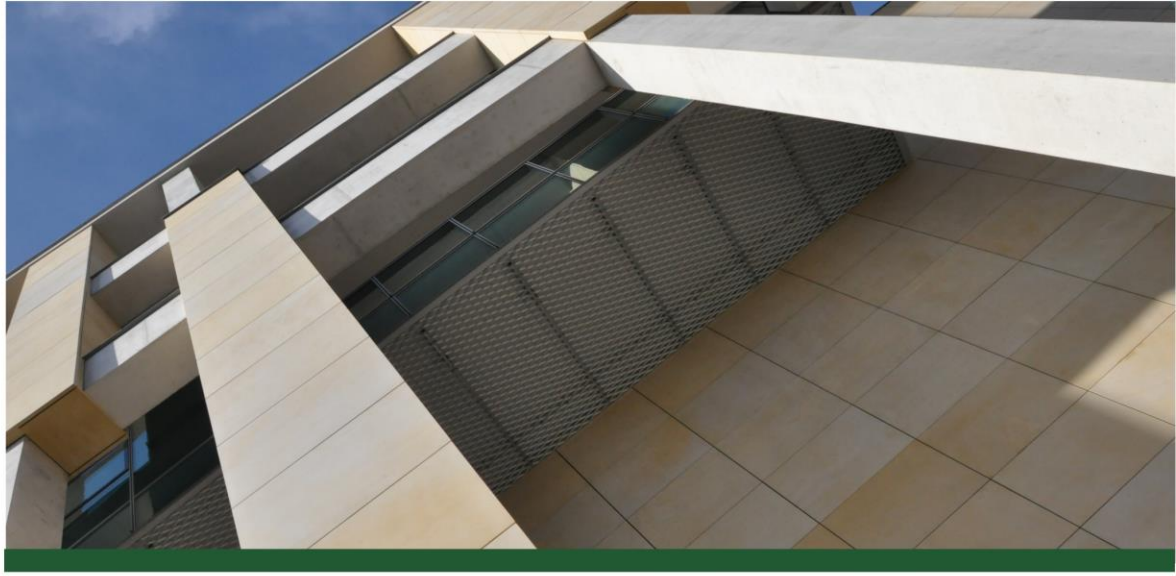

Classifying equity mutual funds according to various risk measures using neural networks

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Motivation for research

- The level of risk determines the investment goals and investment style of mutual funds,

  but it is often changed by managers to earn higher returns – they do so called *style drift*
  - Brown et al. (1996), Chevalier i Allison (1997), Bams, Otten & Ramezanifar (2016), Cao, Iliev & Velthuis (2017), Sha (2020)

Motivation for research

- Rankings of ranking agencies, e.g. Morningstar, vary from eachother
  and there is no consensus whether investors rely on them or not:
  - Ben-David et al. (2018) – investors rely on rankings more than on a fund's exposure to risk factors
  - Barber, Huang& Odean (2016), Berk & Van Binsbergen (2016): only the best informed investors have tools to monitor fund managers
  - Huang et al. (2020) – investors are rational and react optimally on the ranking stars of Morningstar

Motivation for research

- Our previous study on Polish equity mutual funds confirms that various attributes explain the risks taken by these funds and that classification of funds according to risk is correct
  - Perez i Szczyt (2021): more applicable results in case of *standard deviation* than in case of *beta ratio*

Research question

- Which attributes/variables of mutual funds explain their classification according to risk measures?
  - Are these attributes *informative/valuable* to investors, so they can use them when they buy mutual funds?

- Does machine learning helps to answer this question?

Data

Morninstar Direct database:

- Open end investment funds registered in Europe
- *equity* funds
- *oldest share* funds
- inception before 01.01.2021 (24 917 funds)
- Sales region – European cross border (very popular recently)

6689 equity funds of European cross border sales region

- Monthly data from January 1990 to July 2023
- Data without survivalship bias

32 899 observations

Data

Quantitative variables:

- Rt – annual rate of return obtained on the basis of monthly data
- Age – operating time counted in years
- Size – fund's net assets (NAV)
- CF – cash flow

$$CF_{i,t} = \frac{NAV_{i,t} - NAV_{i,t-i}(1 + R_{i,t})}{NAV_{i,t-i}}$$

Additionally, the following was used as an input variable:

- Time (year to which a specific observation refers)

Data

	N	Average	Mediane	25% perc.	75% perc.	St. dev.
NAV (euro)	54623	131 777 898	28 558 862	7 528 274	98 464 946	42 299 045
CF	54623	0,74	0,88	-0,48	1,92	4,53
Rt	78067	0,528	0,809	-0,477	1,764	2,178
Age (Years)	78067	8,8	7	3	13	8

Data

Qualitative variables:

- Currency – the base currency of a fund
- Category – the category to which a fund belongs
- Domicile – location of fund registration
- Legal form of a fund

Data

Qualitative variables:

- Currency – the base currency of a fund (17 categories)

Currency	share in database
Euro	55%
US Dollar	29%
Pound Sterling	9%
Swiss Franc	3%
Japanese Yen	2%
Swedish Krona	1%
Norwegian Krone	1%
Other	1%

Data

Qualitative variables:

- Category – the category to which a fund belongs (38 categories)

Category	share in database
Global Equity Large Cap	19%
Europe Equity Large Cap	17%
Global Emerging Markets Equity	8%
Europe Equity Mid/Small Cap	6%
Long/Short Equity	4%
US Equity Large Cap Blend	4%
Asia ex-Japan Equity	4%
Japan Equity	4%
Global Equity Mid/Small Cap	3%
Other	27%
No info	4%

Data

Qualitative variables:

- Domicile (25 categories)

Domicile	share in database
Luxembourg	54%
Ireland	18%
France	6%
United Kingdom	5%
Germany	5%
Austria	4%
Belgium	3%
Liechtenstein	2%
Switzerland	1%
Netherlands	1%
Denmark	1%
Other	2%

Data

Qualitative variables:

- Legal form of a fund (7 categories)

Legal form	share in database
SICAV	48%
Open Ended Investment Company	32%
FCP	14%
Unit Trust	5%
Other	0,04%

Data

Output variables - classifiers:

1. Beta – coefficient determining the degree of relationship between the fund's return and the market's return (MSCI Europe)

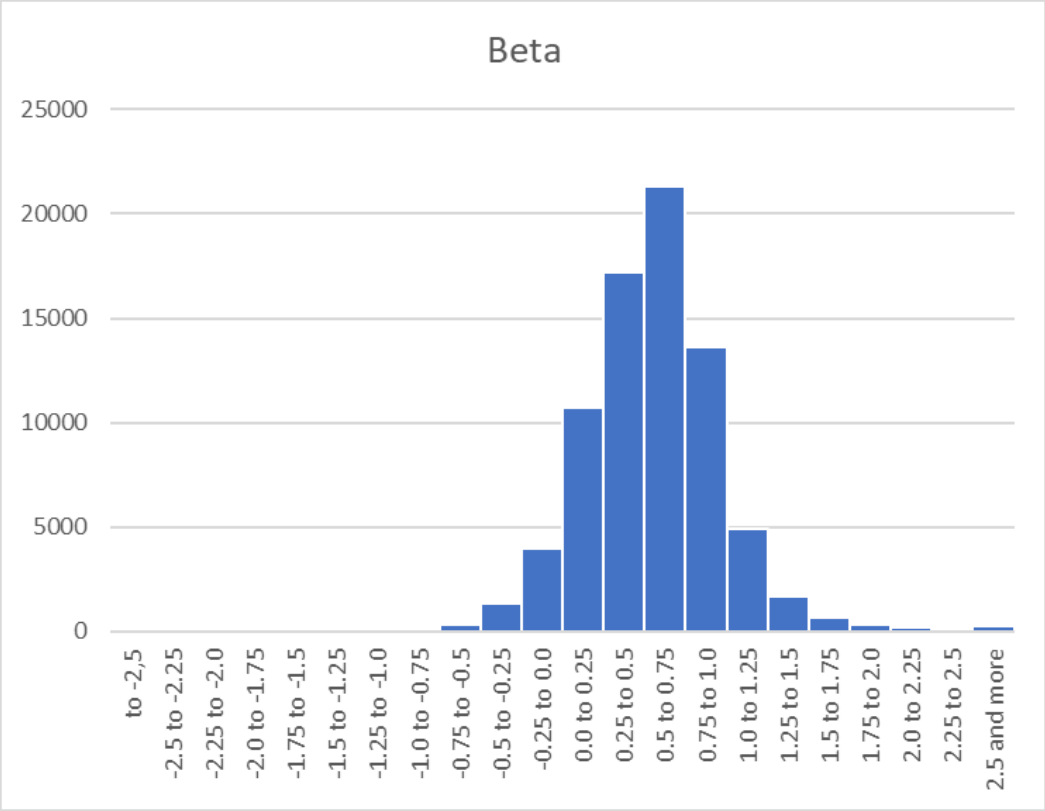
1: Beta < 0
2: Beta $\in$ <0 ; 0,5)
2: Beta $\in$ <0,5 ; 1)
4: Beta > 1

2. Sigma – standard deviation of monthly returns in particular years

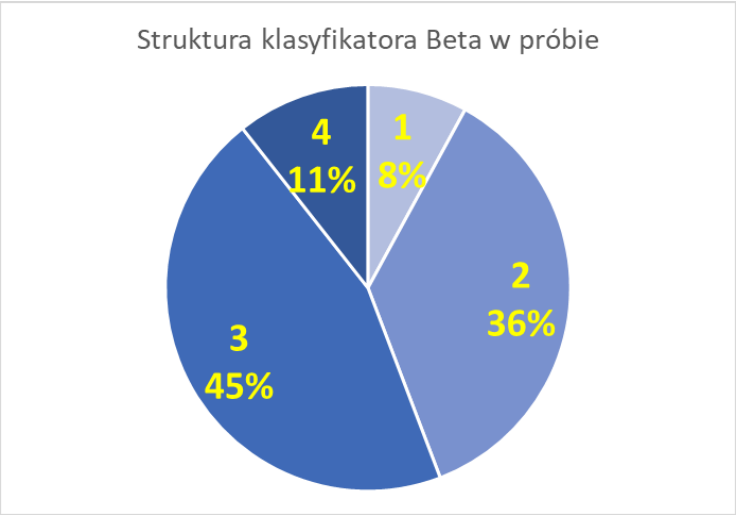
1: Sigma < 2
2: Sigma $\in$ <2 ; 4)
2: Sigma $\in$ <4 ; 6)
4: Sigma > 6

Data

Output variables - classifiers:



średnia	0,54
mediana	0,55
25% perc.	0,29
75% perc.	0,79



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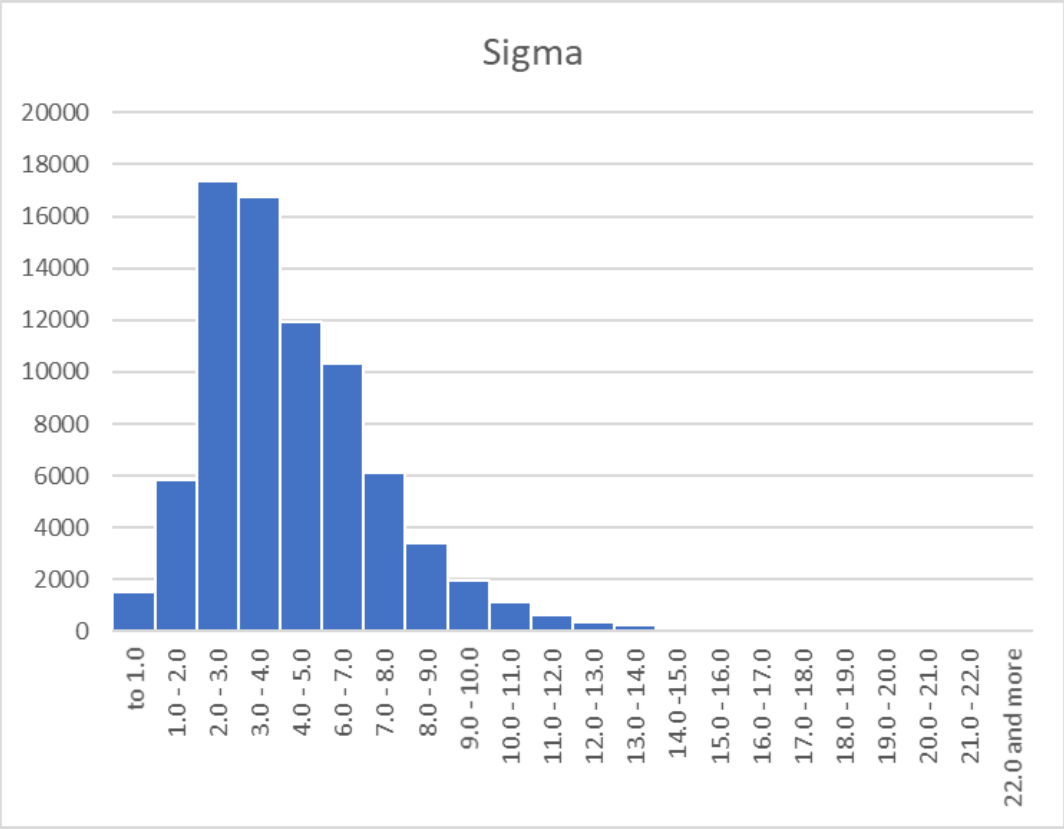
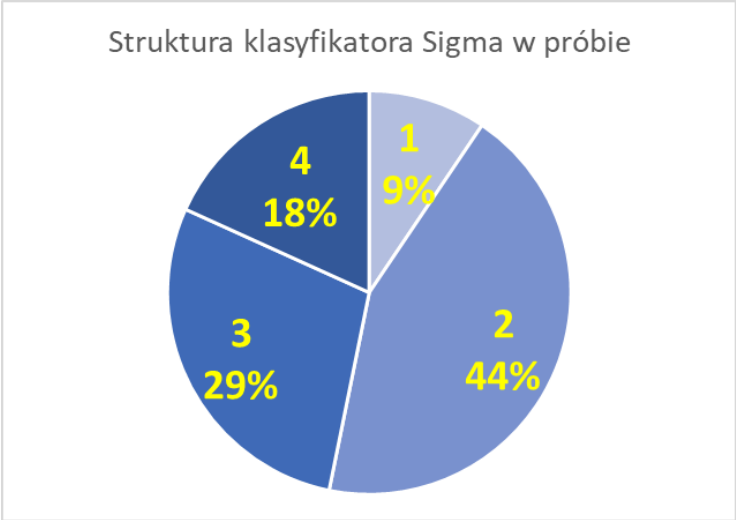
Output variables - classifiers:



średnia	4,30
mediana	3,82
25% perc.	2,72
75% perc.	5,45



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Output variables - classifiers:

3. SSD – semistandard deviation of monthly returns from the mean

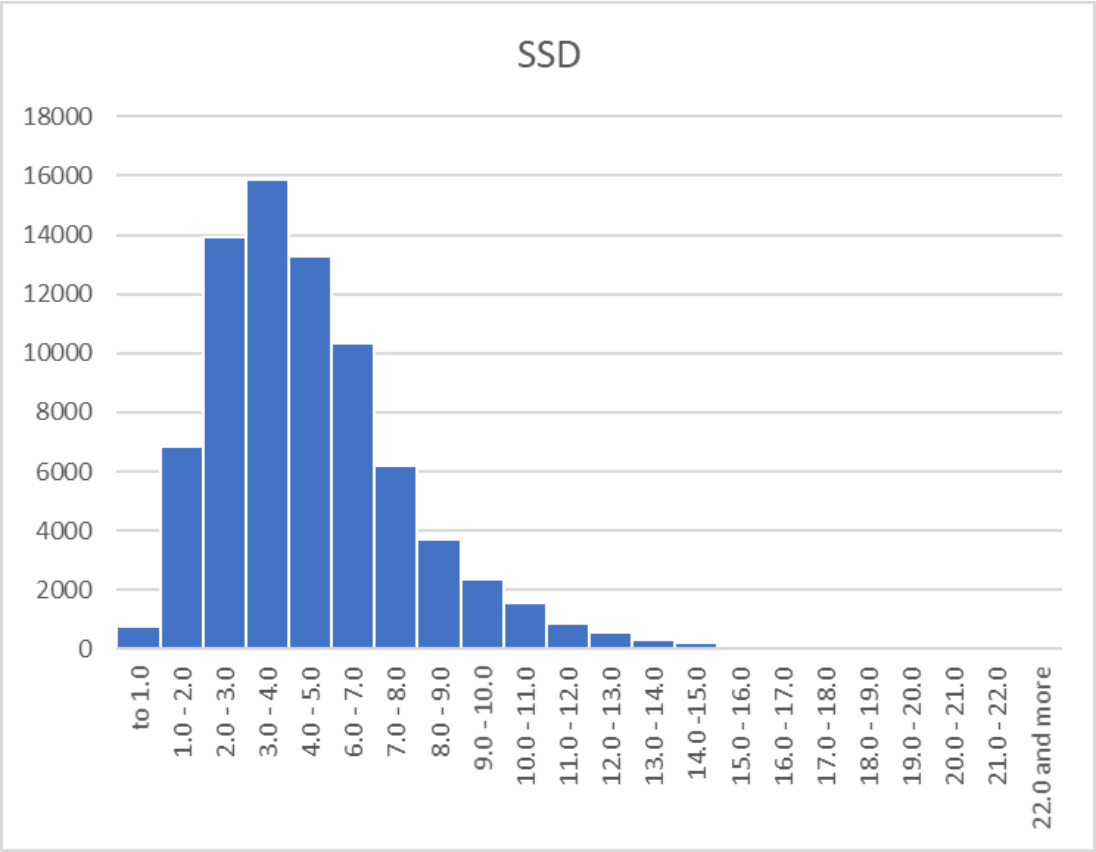
1: SSD < 2,5
2: SSD $\in$ <2,5 ; 4)
2: SSD $\in$ <4 ; 6,5)
4: SSD > 6,5

2. VaR – estimated using the parametric method, with a confidence level of 0.95

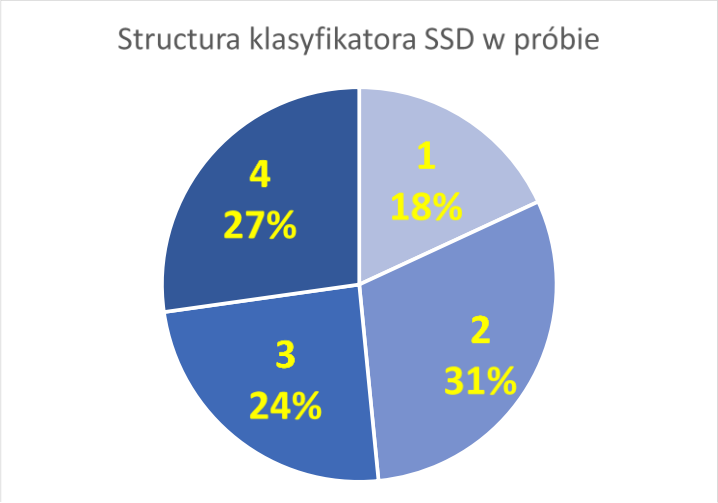
1: VaR < -9
2: VaR $\in$ <-9 ; -6)
2: VaR $\in$ <-6 ; -3)
4: VaR > -3

Data

Output variables - classifiers:



średnia	4,54
mediana	4,08
25% perc.	2,86
75% perc.	5,67



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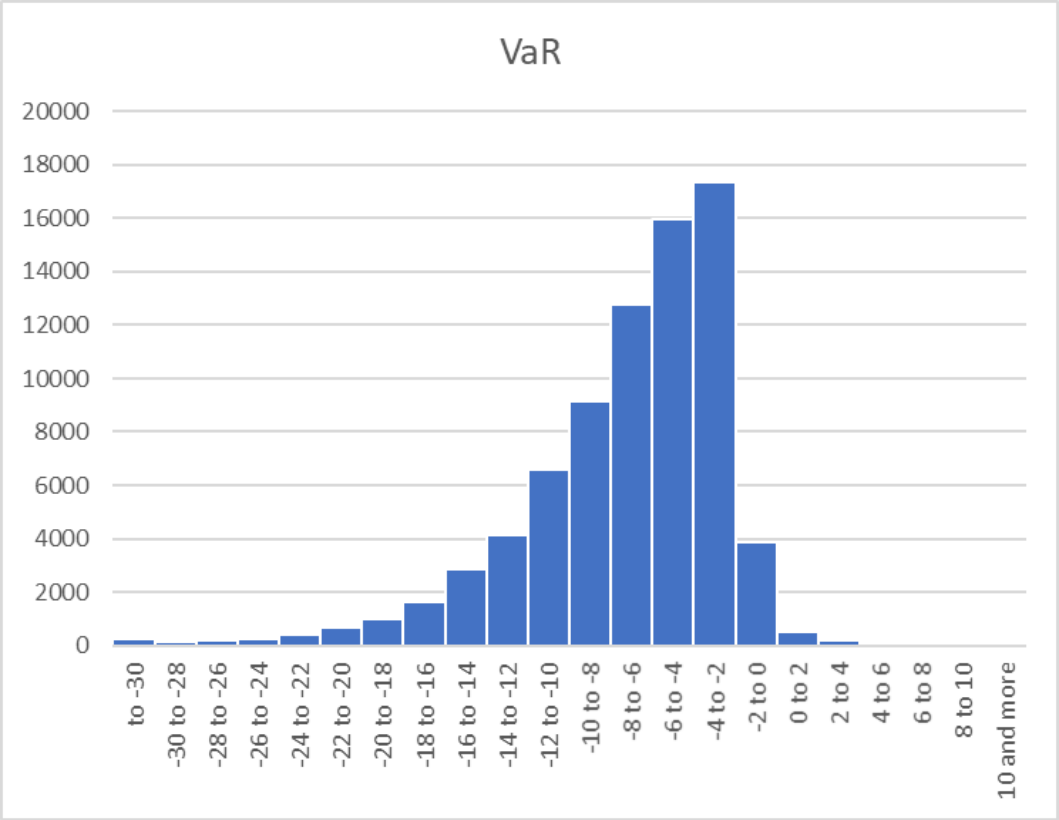
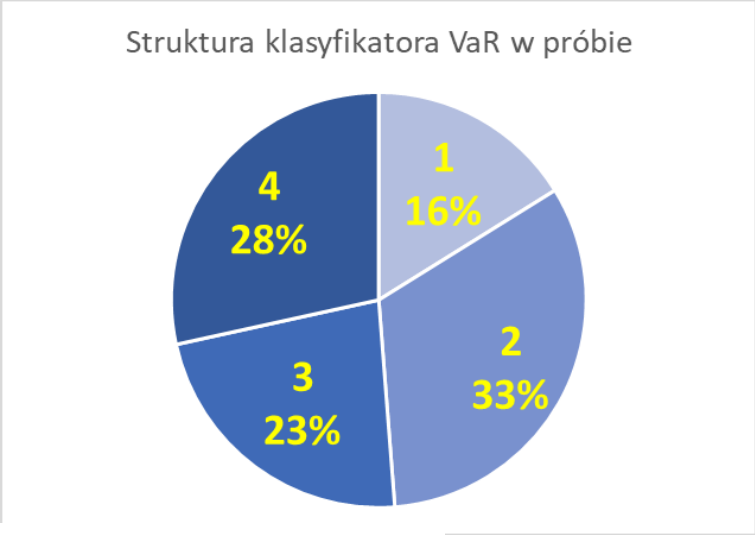
Data

Output variables - classifiers:



średnia	-7,26
mediana	-6,13
25% perc.	-9,64
75% perc.	-3,72



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Research procedure

- *Statistica.PL,* artificial neural networks module
- Automatic network search procedure was used
- It was allowed to build both MLP (multi-layer networks) and RBF (networks with one hidden layer).
- The number of hidden neurons was limited to the range of 4-13 for the MLP and 10-20 for the RBF
- Various activation functions have been adopted (linear, logistic, exponential, hyperbolic tangent)

Research procedure

- From all possible combinations of parameters, 30 networks were randomly selected, of which the 5 best ones were selected for the final classification (providing the best classification correctness).
- Classification was performed based on the network team
  - i.e. the fund was assigned to the class that was indicated by the largest number of networks

Results

<u>Beta classificator</u>

Overall classification accuracy – **68%**

Class 1 – 25% Class 2 - 66%

Class 3 – 85% Class 4 – 9%

- Global sensitivity analysis showed that in this classification, the attributes that differentiated the groups were primarily:

  currency (1,83), category (1,62), domicile (1,55), legal form (1,31) i time (1,24).

Results

<u>Sigma classificator</u>

Overall classification accuracy – **60%**

Class 1 – 9% Class 2 - 88%

Class 3 – 41% Class 4 – 32%

- Global sensitivity analysis showed that in this classification, the attributes that differentiated the groups were primarily:

  currency (1,38), legal form (1,31), category (1,30), domicile (1,18) and return (1,12).

Results

SSD classificator

Overall classification accuracy – **47%**

Class 1 – 41% Class 2 - 69%

Class 3 – 25% Class 4 – 46%

- Global sensitivity analysis showed that in this classification, the attributes that differentiated the groups were primarily:

  currency (1,26), category (1,17) and domicile (1,17).

Results

<u>VaR classificator</u>

Overall classification accuracy – **54%**

Class 1 – 29% Class 2 - 84%

Class 3 – 17% Class 4 – 63%

- Global sensitivity analysis showed that in this classification, the attributes that differentiated the groups were primarily:

  legal form (1,30), return (1,22), category (1,20), currency (1,18), domicile (1,14).

Results

Classificator	Accuracy	Main explaining variables/attributes
Beta	68%	Currency, category, domicile, legal form, time
Sigma	60%	Currency, legal form, category, domicile, return
SSD	47%	Currency, category, domicile
VaR	54%	Legal form, return, category, currency, domicile

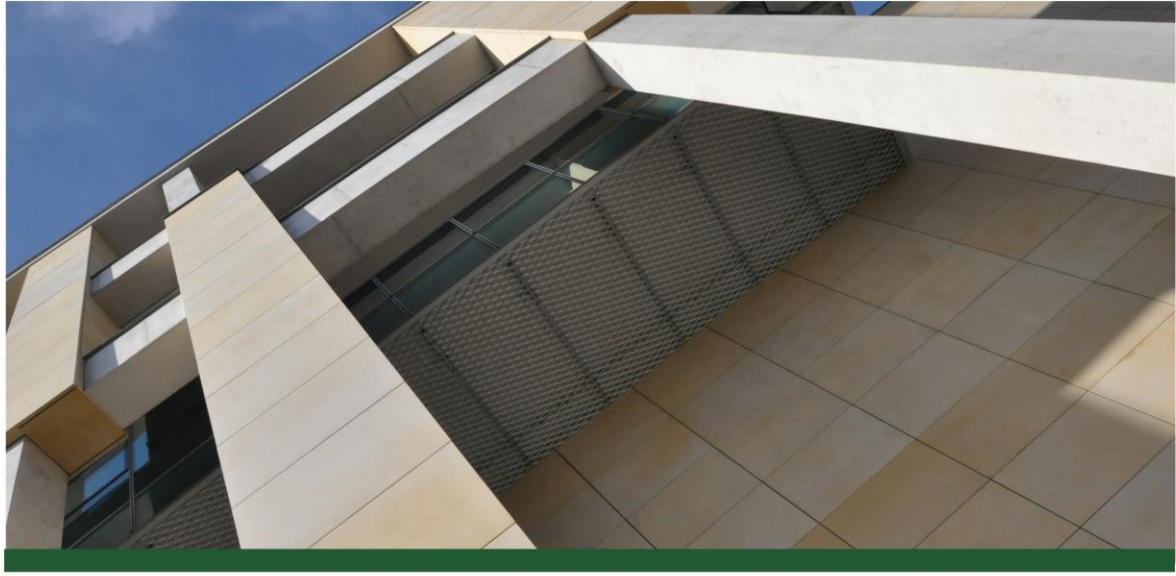
- The lowest value for classification showed Cash Flow (0,99).

Conclusions

- The methods used and the input variables used for classification **do not give very good results**, although these results are significantly better than random classification.
- The qualitative variables used, which are rather constant characteristics of funds over time, work much better in predicting the fund's risk - compared to quantitative variables.
- Classifying a fund into a category determining its risk, based on data that are not typical risk measures, may involve a noticeable probability of making an error.
- The classification based on the proposed methods is still better than random classification

Further research

- Switch from analysis based on annual data to monthly data.
- Expanding the sample to other stock markets and other types of mutual funds
- Searching for additional variables characterizing funds



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Thank you!

We appreciate comments and suggestions!

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