Query Performance Prediction

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DPJ482

ABSTRACT

This paper examines the possibility of using standard deviation as a post retrieval query performance predictor, and comparing the result with median absolute deviation. Using these as a predictor is much cheaper computational wise. The study used several used Precision at 5 and Bpref to test if there was a correlation. The study was unable to conclude anything, but found some fields that may be interesting for further studies.

1. INTRODUCTION

The world is heavily dependant on search engines. Because of this, it is of increasing importance that search engines provide the best possible result for all queries. This leads to increasing demands for information retrieval (IR) systems, when predicting the successfulness of new approaches.

Query performance prediction (QPP) is one approach for testing approaches. This approach is used to calculate the performance of a query before or after it's put through the IR system. Using QPP it is possible to choose strategy with a queries to improve the IR systems performance and successfulness. One way would be to redemptive try to predict how a query would perform with several different search engines. Then the system could choose the one IR system the prediction would perform the best width.

There are several studies about QPP, and a study by Hauff and Azzopardi[2] test whether or not there is actually any need for us to apply QPP. They investigate when there is a reason to even try to apply QPP on search queries to increase performance. They conclude that even QPP can increase IR systems performance, it only applies when Kendall's Tau correlation of $\tau >= 0.5$ is achieved by the IR system. Because of this they claim that QPP does not lead to any significant increase in query performance, but rather leads to a decrease, as many State of the art IR systems do not acheive the before mentioned τ value yet.

In another article by Hauff, Hiemstra, and Jong[3], they study the how pre-retrieval query performance. They measure how several pre-retrieval IR systems perform on several document and query collections, to see if an extra layer of IR with pre-retrieval QPP can be increase the performance of the IR system. There is no real conclusions, as many preretrieval strategies only increased the performance with some collections, while they actually reduced the performance with others.

In this article from Pérez-Iglesias and Araujo[4] they propose that the score deviation of QPP can be used to estimate the effectiveness of the QPP for post retrieval QPP. They examine the correlation between different QPP effectiveness and their QPP score deviation, to see if a more diverse scoring leads to better results, which they conclude it does.

The previous article lead us to the experiment on which this paper is based upon. The article by Cummins er. al. [1] examines standard deviation as a predictor for the QPP performance. They conclude that using the standard deviation it better and cheaper as a post retrieval method for queries of short or medium length, and is much cheaper to calculate, than many other post retrieval QPP.

The previous article lead us to this article where we then want to investigate their claims, and compare them to another deviation score, to see if we can both replicate their result, and how their result compares to another deviation calculation.

2. METHODOLOGY

The standard deviation proposed by Cummins et. al. use several different cut-off points, in the range 10% to 90% of the top retrieved documents. Then calculating the standard deviation on only the top documents per query. This results is then correlated with the average precision. This is done for both the normal standard deviation, but also the normalised standard deviation. It will be normalised with the Query length.

$$n(\sigma_{x\%}) = \frac{\sigma_{x\%}}{\sqrt{Querylength}}$$

These results are then compared to another deviation function, the median absolute deviation(MAD) function. It is described as follows

$$\text{MAD} = \text{median}\left(x_i - \text{median}(x)\right) \tag{1}$$

The whole experiment is replicated using the MAD to see if I can achieve the same or better correlation.

3. DATA SETS & QUERIES

Information Retrieval 2016 DIKU, Denmark
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The data used in this paper is a collection of TREC collections with a large amount of documents, and varying document length and length deviation to test the prediction in many situations. Table 1 shows an overview of the data.

Table 1: Document data sets

Name	laTimes	fbis	ft
document count	131896	130471	210158
average length	502	504	399
minimum length	2	12	11
maximum	24125	143175	26145

The queries look like this

Table 2: queries data set

Name	queries
document count	150
average length	19.54

Furthermore, list the number of queries and the average query length for the superset of the queries.

4. EXPERIMENTAL SETUP

For all comparisons I use the Krovetz stemmer, and use Okapi BM25 with k1=1.2,b=0.75 and k3 = 7 using the Indri to calculate all this. I use c++ and Python in unison with Indri to reprocess and present the findings done by Indri. The query performance is calculated using TREC_EVAL.

5. EXPERIMENT

For each Collection, the top $N = 20, 50, 100, 200$ documents were retrieved for each query. For each N, top documents were then cut based on $\sigma = 0.1, 0.3, 0.5, 0.7, 0.9$. The standard deviation and MAD was then calculated at precision at 10(P@10) and the bpref. The same thing was then done using the normalized standard deviation and MAD.

Unfourtunatly I was not able to compare my findings with other QPP methods such as Simplified score predictions, Query scope, and σ_{max}.

6. RESULTS

Looking at the results in the table sections, it is hard to draw any conclusions. The best performance are not constrained to a certain part. The only tendency i can derive from the tables is, that the normalized versions tends to be a better predictor. This is true for both the LATIMES collection and the FBIS collection, but is not true for the FT collection.

Furthermore I have no other Post retrieval QPP scores to compare my findings with, which makes me unable to make any conclusions based on my numbers. My numbers are also not as strong as those found by Cummins et. al, and My numbers do not reflect their preference for $\sigma_{50\%}$

It can be observed that collections do not handle the normalization in the same way. The LATIMES and FBIS collections have a tendency to favour the normalized version, while the FT collection favours the standard verison. Why this happens is not concluded.

7. CONCLUSION

Testing if the findings done by Cummins et. al.[1] can be reproduced using other data sets and comparing Standard deviation width Median absolute deviation, to see if it can also be used as a predictor. There is a tendency that median absolute deviation outperforms standard deviation for some collections, so it could be worth looking into when and why this happens.

8. REFERENCES

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9. TABLES

	$\sigma_{10\%}$	$\sigma_{30\%}$	$\sigma_{50\%}$	$\sigma_{70\%}$	$\sigma_{90\%}$	n($\sigma_{10\%}$)	n($\sigma_{30\%}$)	n($\sigma_{50\%}$)	n($\sigma_{70\%}$)	n($\sigma_{90\%}$)
la										
Pearsons	0.3273	0.3379	0.3249	0.2384	0.0335	0.3779	**0.3932**	0.3866	0.3138	0.0633
Spearman	0.4083	0.4138	0.4045	0.2606	-0.0309	0.4283	**0.4334**	0.4279	0.3039	0.006
ft										
Pearsons	0.334	**0.3345**	0.3055	0.3095	0.2253	0.3108	0.3118	0.295	0.2963	0.196
Spearman	**0.4443**	0.444	0.4277	0.3513	0.1702	0.4299	0.4297	0.4136	0.3394	0.168
fbis										
Pearsons	0.1911	0.1794	0.1327	0.0832	0.3151	0.2145	0.2044	0.1579	0.1025	**0.344**
Spearman	0.1307	0.1204	0.0994	0.0719	0.2911	0.1532	0.1416	0.1278	0.1082	**0.3224**

Table 3: $\sigma_{\%}$ correlations for k=20 with P_10 using SD

	$\sigma_{10\%}$	$\sigma_{30\%}$	$\sigma_{50\%}$	$\sigma_{70\%}$	$\sigma_{90\%}$	n($\sigma_{10\%}$)	n($\sigma_{30\%}$)	n($\sigma_{50\%}$)	n($\sigma_{70\%}$)	n($\sigma_{90\%}$)
la										
Pearsons	0.3686	0.3734	0.3665	0.2312	0.1115	0.3923	**0.3927**	0.3795	0.2971	0.1343
Spearman	0.3464	0.3464	0.3625	0.2578	0.0409	0.3623	0.3625	**0.3711**	0.2685	0.0493
ft										
Pearsons	0.2388	0.2277	0.2185	**0.277**	0.2452	0.2071	0.1991	0.2055	0.2561	0.216
Spearman	0.3025	0.3032	**0.3437**	0.32	0.1657	0.2847	0.2862	0.3237	0.2948	0.1678
fbis										
Pearsons	0.2852	0.2735	0.2008	0.105	0.3691	0.2962	0.2891	0.2236	0.1169	**0.3867**
Spearman	0.1882	0.1807	0.1583	0.111	0.335	0.1955	0.1869	0.1651	0.1266	**0.3476**

Table 4: $\sigma_{\%}$ correlations for k=20 with P_10 using MAD

	$\sigma_{10\%}$	$\sigma_{30\%}$	$\sigma_{50\%}$	$\sigma_{70\%}$	$\sigma_{90\%}$	n($\sigma_{10\%}$)	n($\sigma_{30\%}$)	n($\sigma_{50\%}$)	n($\sigma_{70\%}$)	n($\sigma_{90\%}$)
la										
Pearsons	0.5051	0.5229	0.4614	0.2254	0.0955	0.612	**0.6352**	0.5838	0.3313	0.145
Spearman	0.4437	0.4518	0.4402	0.2523	-0.0256	0.4527	**0.461**	0.4541	0.2753	0.0026
ft										
Pearsons	0.4964	**0.4966**	0.4669	0.2518	0.2168	0.4648	0.4655	0.4472	0.2365	0.1889
Spearman	**0.5006**	0.4998	0.4791	0.366	0.1712	0.4942	0.4939	0.4774	0.3696	0.179
fbis										
Pearsons	0.4456	0.4251	0.3526	0.1316	0.197	**0.5049**	0.4854	0.4063	0.1776	0.2408
Spearman	0.2012	0.19	0.1716	0.117	0.2495	0.2309	0.2186	0.2081	0.1598	**0.2854**

Table 5: $\sigma_{\%}$ correlations for k=20 with bpref using SD

	$\sigma_{10\%}$	$\sigma_{30\%}$	$\sigma_{50\%}$	$\sigma_{70\%}$	$\sigma_{90\%}$	n($\sigma_{10\%}$)	n($\sigma_{30\%}$)	n($\sigma_{50\%}$)	n($\sigma_{70\%}$)	n($\sigma_{90\%}$)
la										
Pearsons	0.528	0.5405	0.5017	0.315	0.1557	0.5941	**0.5998**	0.5607	0.4058	0.1889
Spearman	0.4262	0.4275	0.4151	0.2603	0.0594	0.4331	**0.4339**	0.4146	0.261	0.0654
ft										
Pearsons	**0.4092**	0.3982	0.3785	0.3002	0.2105	0.3577	0.351	0.3607	0.2789	0.1921
Spearman	0.3671	0.3681	**0.4055**	0.362	0.16	0.3588	0.3606	0.3957	0.3542	0.1648
fbis										
Pearsons	0.4142	0.3827	0.2909	0.1496	0.2811	**0.4713**	0.4436	0.3425	0.1881	0.3168
Spearman	0.1823	0.1744	0.1936	0.1593	0.2885	0.197	0.188	0.2094	0.1822	**0.3049**

Table 6: $\sigma_{\%}$ correlations for k=20 with bpref using MAD

	$\sigma_{10\%}$	$\sigma_{30\%}$	$\sigma_{50\%}$	$\sigma_{70\%}$	$\sigma_{90\%}$	n($\sigma_{10\%}$)	n($\sigma_{30\%}$)	n($\sigma_{50\%}$)	n($\sigma_{70\%}$)	n($\sigma_{90\%}$)
la										
Pearsons	0.4142	0.4007	0.3591	0.2383	0.0282	**0.4517**	0.4488	0.4157	0.3186	0.058
Spearman	0.4078	0.4076	0.3914	0.2596	-0.032	0.4303	**0.4347**	0.4281	0.3147	0.0058
ft										
Pearsons	0.3449	**0.3544**	0.3364	0.3057	0.2186	0.3055	0.3177	0.3231	0.2884	0.1888
Spearman	0.44	**0.4407**	0.4401	0.3385	0.1642	0.4282	0.4294	0.4229	0.3259	0.1663
fbis										
Pearsons	0.2144	0.1982	0.1501	0.1175	0.3172	0.2348	0.2299	0.1826	0.1405	**0.3459**
Spearman	0.1817	0.1769	0.1532	0.119	0.2976	0.1927	0.183	0.1695	0.1516	**0.3308**

Table 7: $\sigma_{\%}$ correlations for k=50 with P_10 using SD

	$\sigma_{10\%}$	$\sigma_{30\%}$	$\sigma_{50\%}$	$\sigma_{70\%}$	$\sigma_{90\%}$	n($\sigma_{10\%}$)	n($\sigma_{30\%}$)	n($\sigma_{50\%}$)	n($\sigma_{70\%}$)	n($\sigma_{90\%}$)
la										
Pearsons	0.3824	0.3698	0.4077	0.2335	0.1067	0.4113	0.398	**0.4147**	0.2972	0.1295
Spearman	0.2571	0.253	0.3512	0.2385	0.0393	0.283	0.2821	**0.3833**	0.2563	0.0486
ft										
Pearsons	0.1693	0.1787	0.2528	**0.2633**	0.2411	0.1188	0.1369	0.2258	0.2417	0.2113
Spearman	0.2317	0.2458	**0.3577**	0.2708	0.1622	0.2135	0.2293	0.338	0.2536	0.1675
fbis										
Pearsons	0.1314	0.1447	0.1763	0.1028	0.3706	0.1608	0.1857	0.213	0.1167	**0.3879**
Spearman	0.1871	0.1692	0.2139	0.0994	0.3439	0.2046	0.1828	0.2288	0.1218	**0.3585**

Table 8: $\sigma_{\%}$ correlations for k=50 with P_10 using MAD

	$\sigma_{10\%}$	$\sigma_{30\%}$	$\sigma_{50\%}$	$\sigma_{70\%}$	$\sigma_{90\%}$	n($\sigma_{10\%}$)	n($\sigma_{30\%}$)	n($\sigma_{50\%}$)	n($\sigma_{70\%}$)	n($\sigma_{90\%}$)
la										
Pearsons	0.5299	0.5325	0.4553	0.2474	0.0954	0.6207	**0.6362**	0.5728	0.3594	0.1464
Spearman	0.4326	0.4424	0.4156	0.2595	0.0018	0.4555	**0.4697**	0.4554	0.3112	0.0534
ft										
Pearsons	0.463	**0.464**	0.4169	0.2197	0.2331	0.4167	0.4224	0.401	0.2065	0.2074
Spearman	**0.4639**	0.4639	0.4469	0.3295	0.1955	0.4499	0.4497	0.4331	0.3266	0.2019
fbis										
Pearsons	0.3746	0.3603	0.3145	0.1728	0.2613	0.4045	**0.4081**	0.3621	0.2042	0.2963
Spearman	0.2297	0.2255	0.2078	0.1574	0.266	0.2467	0.2374	0.2306	0.1901	**0.3036**

Table 9: $\sigma_{\%}$ correlations for k=50 with bpref using SD

	$\sigma_{10\%}$	$\sigma_{30\%}$	$\sigma_{50\%}$	$\sigma_{70\%}$	$\sigma_{90\%}$	n($\sigma_{10\%}$)	n($\sigma_{30\%}$)	n($\sigma_{50\%}$)	n($\sigma_{70\%}$)	n($\sigma_{90\%}$)
la										
Pearsons	0.3945	0.3794	0.4825	0.2958	0.165	0.4727	0.4606	**0.5476**	0.3905	0.2001
Spearman	0.2542	0.2508	0.3366	0.235	0.0789	0.2845	0.2857	**0.374**	0.2545	0.0982
ft										
Pearsons	0.2755	0.2888	**0.3342**	0.2627	0.2163	0.2146	0.2398	0.3158	0.2474	0.1972
Spearman	0.2938	0.3032	**0.3981**	0.2854	0.1642	0.2803	0.2921	0.3845	0.2786	0.171
fbis										
Pearsons	0.2381	0.2339	0.2824	0.1626	0.3082	0.2846	0.2955	0.3296	0.1878	**0.331**
Spearman	0.1929	0.1717	0.2283	0.1621	0.3025	0.2162	0.1917	0.2564	0.1868	**0.3206**

Table 10: $\sigma_{\%}$ correlations for k=50 with bpref using MAD

	$\sigma_{10\%}$	$\sigma_{30\%}$	$\sigma_{50\%}$	$\sigma_{70\%}$	$\sigma_{90\%}$	n($\sigma_{10\%}$)	n($\sigma_{30\%}$)	n($\sigma_{50\%}$)	n($\sigma_{70\%}$)	n($\sigma_{90\%}$)
la										
Pearsons	0.4016	0.382	0.3533	0.2311	0.0253	**0.4409**	0.4376	0.4138	0.3132	0.0548
Spearman	0.3917	0.3917	0.3738	0.2583	-0.0337	0.4236	**0.4285**	0.4199	0.3055	0.0039
ft										
Pearsons	0.3328	0.3374	**0.3403**	0.3068	0.2171	0.2785	0.2904	0.3231	0.2883	0.187
Spearman	0.401	0.4111	**0.4253**	0.3285	0.1639	0.381	0.3881	0.4079	0.3194	0.1669
fbis										
Pearsons	0.2382	0.232	0.1837	0.1321	0.3174	0.2532	0.2605	0.2166	0.1562	**0.346**
Spearman	0.2141	0.21	0.1929	0.1341	0.2988	0.2314	0.2272	0.2189	0.1736	**0.3332**

Table 11: $\sigma_{\%}$ correlations for k=100 with P_10 using SD

	$\sigma_{10\%}$	$\sigma_{30\%}$	$\sigma_{50\%}$	$\sigma_{70\%}$	$\sigma_{90\%}$	n($\sigma_{10\%}$)	n($\sigma_{30\%}$)	n($\sigma_{50\%}$)	n($\sigma_{70\%}$)	n($\sigma_{90\%}$)
la										
Pearsons	0.2708	0.3171	0.3954	0.2268	0.1042	0.2944	0.3511	**0.4062**	0.2923	0.127
Spearman	0.2192	0.2798	0.3305	0.2319	0.0368	0.236	0.3011	**0.3656**	0.2506	0.046
ft										
Pearsons	0.0658	0.1572	**0.2635**	0.2543	0.2395	0.0182	0.1084	0.2292	0.2313	0.2094
Spearman	0.1196	0.1869	**0.3527**	0.2418	0.1585	0.1184	0.1808	0.3379	0.2303	0.1639
fbis										
Pearsons	0.2276	0.28	0.2434	0.1127	0.3706	0.2191	0.2824	0.2673	0.1252	**0.3877**
Spearman	0.2127	0.2153	0.2495	0.1019	0.3456	0.2277	0.2273	0.2661	0.1333	**0.3597**

Table 12: $\sigma_{\%}$ correlations for k=100 with P_10 using MAD

	$\sigma_{10\%}$	$\sigma_{30\%}$	$\sigma_{50\%}$	$\sigma_{70\%}$	$\sigma_{90\%}$	n($\sigma_{10\%}$)	n($\sigma_{30\%}$)	n($\sigma_{50\%}$)	n($\sigma_{70\%}$)	n($\sigma_{90\%}$)
la										
Pearsons	0.485	0.4731	0.4151	0.2416	0.0928	0.574	**0.5825**	0.532	0.3513	0.1396
Spearman	0.4167	0.4264	0.39	0.2508	0.0147	0.4481	**0.463**	0.4399	0.3019	0.0673
ft										
Pearsons	0.4026	**0.4048**	0.3739	0.1979	0.2535	0.3465	0.3587	0.3576	0.1862	0.2305
Spearman	0.4035	**0.4139**	0.3974	0.2951	0.2121	0.3879	0.3928	0.3826	0.2939	0.2179
fbis										
Pearsons	0.352	0.349	0.3188	0.181	0.2906	0.3674	**0.3832**	0.3576	0.2053	0.3212
Spearman	0.2365	0.234	0.2305	0.1703	0.2727	0.2588	0.2566	0.258	0.206	**0.3126**

Table 13: $\sigma_{\%}$ correlations for k=100 with bpref using SD

	$\sigma_{10\%}$	$\sigma_{30\%}$	$\sigma_{50\%}$	$\sigma_{70\%}$	$\sigma_{90\%}$	n($\sigma_{10\%}$)	n($\sigma_{30\%}$)	n($\sigma_{50\%}$)	n($\sigma_{70\%}$)	n($\sigma_{90\%}$)
la										
Pearsons	0.3611	0.3586	0.4477	0.2814	0.1698	0.421	0.4333	**0.5097**	0.3734	0.2012
Spearman	0.2958	0.3305	0.3531	0.2266	0.0962	0.3158	0.358	**0.389**	0.2508	0.1157
ft										
Pearsons	0.0496	0.256	**0.3096**	0.2316	0.2374	0.0185	0.2044	0.287	0.2176	0.2207
Spearman	0.1353	0.2288	**0.3827**	0.2447	0.1757	0.1367	0.2274	0.3691	0.2426	0.1832
fbis										
Pearsons	0.3165	0.3442	0.3456	0.1715	0.3161	0.3096	0.3511	**0.3694**	0.1894	0.3332
Spearman	0.2295	0.22	0.2622	0.1671	0.308	0.2508	0.2403	0.286	0.1992	**0.3263**

Table 14: $\sigma_{\%}$ correlations for k=100 with bpref using MAD

	$\sigma_{10\%}$	$\sigma_{30\%}$	$\sigma_{50\%}$	$\sigma_{70\%}$	$\sigma_{90\%}$	n($\sigma_{10\%}$)	n($\sigma_{30\%}$)	n($\sigma_{50\%}$)	n($\sigma_{70\%}$)	n($\sigma_{90\%}$)
la										
Pearsons	0.3767	0.3708	0.3498	0.2226	0.0253	0.4146	**0.4296**	0.4139	0.3067	0.0548
Spearman	0.357	0.3672	0.3658	0.2533	-0.0337	0.3834	**0.4036**	0.4036	0.303	0.0039
ft										
Pearsons	0.3089	0.3261	**0.3461**	0.3022	0.2171	0.2412	0.2741	0.3276	0.2843	0.187
Spearman	0.3512	0.3678	**0.4159**	0.323	0.1639	0.3374	0.3537	0.3997	0.3202	0.1669
fbis										
Pearsons	0.2619	0.2783	0.2007	0.1379	0.3173	0.2757	0.3071	0.2348	0.1626	**0.3459**
Spearman	0.2565	0.2629	0.2196	0.1433	0.2988	0.2692	0.2705	0.244	0.1841	**0.3332**

Table 15: $\sigma_{\%}$ correlations for k=200 with P_10 using SD

	$\sigma_{10\%}$	$\sigma_{30\%}$	$\sigma_{50\%}$	$\sigma_{70\%}$	$\sigma_{90\%}$	n($\sigma_{10\%}$)	n($\sigma_{30\%}$)	n($\sigma_{50\%}$)	n($\sigma_{70\%}$)	n($\sigma_{90\%}$)
la										
Pearsons	0.2762	0.3543	0.3608	0.2172	0.1042	0.2911	**0.3805**	0.3761	0.2846	0.127
Spearman	0.1418	0.2061	0.2512	0.2182	0.0368	0.1692	0.2349	**0.2896**	0.2385	0.046
ft										
Pearsons	-0.0021	0.1208	**0.2786**	0.2491	0.2395	-0.0335	0.0785	0.242	0.227	0.2094
Spearman	0.0238	0.1237	**0.3543**	0.2232	0.1585	0.0158	0.1125	0.3395	0.2185	0.1639
fbis										
Pearsons	0.2032	0.2921	0.2416	0.1049	0.3704	0.209	0.3091	0.2663	0.1166	**0.3875**
Spearman	0.232	0.2715	0.2545	0.1063	0.3452	0.2417	0.2778	0.2727	0.1356	**0.3594**

Table 16: $\sigma_{\%}$ correlations for k=200 with P_10 using MAD

	$\sigma_{10\%}$	$\sigma_{30\%}$	$\sigma_{50\%}$	$\sigma_{70\%}$	$\sigma_{90\%}$	n($\sigma_{10\%}$)	n($\sigma_{30\%}$)	n($\sigma_{50\%}$)	n($\sigma_{70\%}$)	n($\sigma_{90\%}$)
la										
Pearsons	0.4457	0.4413	0.3906	0.2264	0.0946	0.5306	**0.5504**	0.5075	0.3332	0.1385
Spearman	0.3856	0.4026	0.3582	0.222	0.0185	0.4155	**0.4431**	0.4106	0.2755	0.0704
ft										
Pearsons	0.3345	**0.362**	0.3358	0.1837	0.2535	0.2735	0.3194	0.3219	0.1758	0.2353
Spearman	0.3583	**0.3698**	0.363	0.2757	0.2123	0.3437	0.3555	0.3473	0.2776	0.2173
fbis										
Pearsons	0.3467	0.3582	0.2943	0.175	0.2861	0.3624	**0.3928**	0.3341	0.1992	0.317
Spearman	0.2637	0.2733	0.2408	0.1712	0.2646	0.2886	0.2948	0.276	0.2123	**0.3049**

Table 17: $\sigma_{\%}$ correlations for k=200 with bpref using SD

	$\sigma_{10\%}$	$\sigma_{30\%}$	$\sigma_{50\%}$	$\sigma_{70\%}$	$\sigma_{90\%}$	n($\sigma_{10\%}$)	n($\sigma_{30\%}$)	n($\sigma_{50\%}$)	n($\sigma_{70\%}$)	n($\sigma_{90\%}$)
la										
Pearsons	0.3429	0.3698	0.4031	0.2532	0.1719	0.3907	0.435	**0.4662**	0.3432	0.2012
Spearman	0.2254	0.258	0.2535	0.1898	0.1048	0.2646	0.3009	**0.3038**	0.2162	0.124
ft										
Pearsons	0.0095	0.2267	**0.2844**	0.203	0.2419	-0.012	0.1824	0.2629	0.1931	0.2294
Spearman	0.0775	0.1894	**0.3691**	0.2078	0.1811	0.0756	0.1866	0.3586	0.2128	0.1893
fbis										
Pearsons	0.2975	0.3374	0.3256	0.1549	0.3136	0.3063	**0.3589**	0.3502	0.1722	0.3297
Spearman	0.2588	0.2833	0.263	0.1657	0.3076	0.2766	0.3002	0.2884	0.1967	**0.3264**

Table 18: $\sigma_{\%}$ correlations for k=200 with bpref using MAD