goal based click *smoothing*.

Table 3: Effect of x on percentage improvement in NDCG5 together with click buzz features. Baseline is the same as used in Table 2.

x	Timeouts	Missions	Goals
0.2	0.56 (0.178)	**0.99 (0.005)**	**1.13 (0.001)**
0.4	**0.72 (0.021)**	**1.02 (0.002)**	**0.90 (0.008)**
0.6	**0.87 (0.007)**	**1.05 (0.003)**	**1.12 (0)**
0.8	**0.83 (0.003)**	**1.23 (0)**	**1.57 (0)**
1.0	**0.67 (0.016)**	**1.18 (0)**	**1.08 (0.003)**
1.2	0.63 (0.053)	**0.85 (0.014)**	**1.00 (0.002)**
1.4	**0.85 (0.003)**	**1.07 (0.001)**	**0.98 (0.001)**
1.6	**0.86 (0.006)**	**1.30 (0.0002)**	**0.92 (0.019)**
1.8	**0.75 (0.014)**	**1.03 (0.006)**	**0.94 (0.001)**
2.0	**0.70 (0.027)**	**1.13 (0)**	**0.90 (0.028)**
3.0	**1.04 (0)**	**0.97 (0.004)**	**1.00 (0.010)**
4.0	**0.91 (0.003)**	**1.06 (0.002)**	**1.12 (0.002)**

Discussions and Conclusions

In this study we propose novel temporal click features [3] for recency ranking. Rather than computing simple aggregate click through rates, features are derived using the temporal click through data and query reformulations. One of the features that we use is *click buzz* that captures the spiking interest of a url for a query. We also propose time weighted click through rate which treats recent observations as being exponentially more important. We enrich our click features by following query reformulations which typically benefit the first query in the chain of reformulations. Our experiments demonstrate that these features can improve NDCG5 of a major online search engine's recency ranking by up to 1.57%. As part of future work, we would like to evaluate several other time series properties such as auto-correlation as features for recency ranking. Another interesting problem would be to automatically learn the exponential weighting scheme based on query or query categories. It would be interesting to evaluate these ideas for general web search ranking as well.

[3] Because the proposed click features are all time-sensitive, how fast and often they can be generated seems to be an issue. However, a large-scaled commercial search engine can update the click-based features every hour. Therefore, they can reflect the latest popularity of the documents.

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