Optimizing for productivity in workplace communications recommender systems

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Larger organizations and hybrid workplaces have ushered increased volumes of communications (emails/messages) which introduces a lot of interruptions in the workplace. These communications have varying degrees of urgency for the user, from the most urgent, to ones which can be consumed/responded in a few hours to a few days. Not knowing the urgency and surfacing/responding to all communications immediately leads to loss in productivity due to increasing cognitive overload due to multitasking[1]. Email product features (like focussed inbox) and phone features (eg. focus mode in Apple devices) have started making inroads but provide a limited solution in an individual context.

New product features, jointly designed with recommender systems can help manage this cognitive overload in the workplace, and we would like the community to come together and brainstorm new these opportunities. For example, categorization of email into different levels of importance, as well as batching of communications can limit interruptions; summarization and communication feeds can help highlight important communications. Recommender systems developed in this context need to ensure product features can optimize for organizational objectives across recommender systems in addition to individual objectives. We may also need to optimize for longer term objectives in addition to short term ones as well, and may need additional frameworks for long term organizational outcome measurement and testing. Integration (and in some cases joint optimization) with other recommendation products (eg. calendar management systems, organizational matching systems, org structures) can help provide context for the communications and would help advance the state of the art as well. Finally, recommender systems deployed in this context would need to be interpretable and trainable, which could utilize some of the advances in explainable machine learning models and data programming, for example.

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[1]https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/the-social-economy

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