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Machine Learning 2019: Collaborative filtering combined with machine learning for satisfaction surveys - Baba Mbaye - University of franche-comte, France

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Companies are using satisfaction surveys more and more to improve their sales force. With the development of new technologies, the piloting of these surveys is digitized in a partial way. Piloting these surveys often involves the expertise of a human agent in order to make a judgment on the results obtained from surveys. This is a tedious task for the decision-maker, as it faces a huge and heterogeneous amount of data. This problem may be mitigated by using a recommendation engine based on the unsupervised machine learning algorithm. This recommendation system (RS) will be oriented towards two axes: decision-making (DM) and machine learning (ML). In our approach, we use RS for consistency between the user and the recommended items. ML will allow us to include in our list of recommendations, unexpected items, items that are not derived. Mass customization is getting to be more prevalent than ever. Current suggestion frameworks such as content-based sifting and collaborative sifting utilize distinctive data sources to form proposals. Content-based sifting, makes proposals based on client inclinations for item highlights. Collaborative sifting mirrors user-to-user proposals. It predicts clients inclinations as a direct, weighted combination of other client preferences. Both strategies have restrictions. Content-based sifting can suggest a modern thing, but needs more information of client inclination in arrange to join best coordinate. Comparative, collaborative sifting needs huge dataset with dynamic clients who appraised a product some time recently in arrange to create precise forecasts. Combination of these diverse proposal frameworks called crossover frameworksTo choose critical words, TF-IDF strategy was utilized. It looked for included and vital words to client within the sushi places. TFij stands for include x in record y is number of times the include x shows up in archive y partitioned by number of times that same include showed up in a report. For case word salmon, showed up in a document 5 times. But within the other report it showed up 23 times. At that point, the TFij = 5/23. The archives required to be normalized in arrange to compare longer reports. The more times word show up, more critical it is. However, a few words are more imperative that the others. For case small words “the” might show up a thousand times, but it’s not imperative at all. That’s where the archive recurrence comes in.Content-based approach requires a great sum of data of items’ possess highlights, instead of utilizing users’ intuitive and feedbacks. For illustration, it can be motion picture qualities such as sort, year, executive, on-screen character etc., or printed substance of articles that can extricated by applying Normal Dialect Preparing. Collaborative Sifting, on the other hand, doesn’t require anything else but users’ authentic inclination on a set of things. Since it’s based on verifiable information, the center suspicion here is that the users who have concurred within the past tend to moreover concur within the future. In terms of user inclination, it ordinarily communicated by two categories. Express Rating, may be a rate given by a client to an thing on a sliding scale, like 5 stars for Titanic. This is often the foremost coordinate input from clients to appear how much they like an thing. Certain Rating, proposes clients inclination in a roundabout way, such as page sees, clicks, buy records, whether or not tune in to a music track, and so on.Since sparsity and versatility are the two greatest challenges for standard CF strategy, it comes a more progressed strategy that break down the first inadequate network to low-dimensional networks with latent factors/features and less sparsity. That's Lattice Factorization. Beside tackling the issues of sparsity and adaptability, there’s an natural clarification of why we require low-dimensional lattices to speak to users’ inclination. A client gave great evaluations to motion picture Avatar, Gravity, and Beginning. They are not fundamentally 3 separate suppositions but appearing that this clients can be in favor of Sci-Fi motion pictures and there may be numerous more Sci-Fi motion pictures that this client would like.Not at all like particular motion pictures, inactive highlights is communicated by higher-level traits, and Sci-Fi category is one of inactive highlights in this case. What network factorization in the long run gives us is how much a client is adjusted with a set of inactive highlights, and how much a motion picture fits into this set of idle highlights. The advantage of it over standard closest neighborhood is that indeed in spite of the fact that two clients haven’t appraised any same motion pictures, it’s still conceivable to discover the likeness between them in the event that they share the comparable fundamental tastes, once more idle highlights.vvWhen lattice R is thick, U and V may be effortlessly factorized logically. Be that as it may, a lattice of motion picture evaluations is super scanty. In spite of the fact that there are a few imputation methods to fill in lost values , we are going turn to a programming approach to just live with those lost values and discover calculate lattices U and V. Rather than factorizing R through SVD, we are attempting discover U and V straightforwardly with the objective that when U and V increased back together the yield framework R' is the closest guess of R and no more a scanty framework. This numerical estimation is more often than not accomplished with Non-Negative Lattice Factorization for recommender frameworks since there's no negative values in evaluations.A number of optimization calculations have been prevalent to fathom Non-Negative Factorization. Elective Slightest Square is one of them. Since the misfortune work is non-convex in this case, there's no way to reach a worldwide least, whereas it still can reach a awesome estimation by finding neighborhood minimums. Elective Slightest Square is to hold client figure framework steady, alter thing calculate framework by taking subordinates of misfortune function and setting it rise to to 0, and after that set thing calculate framework steady whereas altering client figure network. Rehash the method by switching and altering frameworks back and forward until meeting. In case you apply Scikit-learn NMF show, you may see ALS is the default solver to utilize, which is additionally called Arrange Plummet. Pyspark moreover offers beautiful flawless deterioration bundles that gives more tuning adaptability of ALS itself. from the algorithmic logic of the recommendation system and to make the system partially autonomous on decision-making (to less involving the recommendation engine). Our approach is divided into a) the recommendation process for decision-making, b) unsupervised ML and c) partial "empowerment" for decision-making.

This work is partly presented at 6th World Machine Learning and Deep Learning Congress October 24-25, 2019 held at Helsinki, Finland.