

CLAIMS

What is claimed is:

1. A method comprising:
generating a plurality of machine-learning (ML) scores by feeding an input feed to a machine learning engine for each video in a set of candidate videos;
wherein the input feed for a particular video in the set of candidate videos includes at least:
one or more raw collaborative filtering features;
a collaborative filtering score that was generated based on the one or more raw collaborative filtering features;
one or more raw content-based filtering features; and
a content-based filtering score that was generated based on the one or more raw content-based filtering features;
when generating the ML score for the particular video, the machine learning engine determining weights to give the collaborative filtering score and the content-based filtering score based, at least in part, on the one or more raw collaborative filtering features and the one or more raw content-based filtering features;
selecting one or more videos, from the set of candidate videos, to recommend to a particular user based, at least in part, on the ML scores;
wherein the method is performed by one or more computing devices.
2. The method of Claim 1 wherein:
the input feed for the particular video includes video-pair-centric metrics for a video pair that includes the particular video and a compared video;
the one or more raw collaborative filtering features include collaborative filtering metrics for the video pair; and
the one or more raw content-based filtering features include content-based filtering metrics for the video pair.
3. The method of Claim 2 wherein the collaborative filtering metrics of the video pair are only updated in response to detecting a new indication of user interest with one or more of the videos in the video pair.

4. The method of Claim 2 wherein the content-based filtering metrics of the video pair are only updated in response to detecting a new change in video metadata for one or more of the videos in the video pair.
5. The method of Claim 2 wherein:
the video-pair-centric metrics of the video pair includes a particular set of metrics; and
the particular set of metrics is maintained for the video pair if and only if the video pair satisfies a particular pairing test.
6. The method of Claim 5 wherein the particular set of metrics includes all of the video-pair-centric metrics.
7. The method of Claim 5 wherein the particular set of metrics includes only one of:
the collaborative filtering metrics for the video pair; and
the content-based filtering metrics for the video pair.
8. The method of Claim 7 further comprising using a second pairing test, that is different than the pair test, to determine whether to maintain, for the video pair, the other of:
the collaborative filtering metrics for the video pair; and
the content-based filtering metrics for the video pair.
9. The method of Claim 1 wherein:
the input feed for the particular video includes a plurality of collaborative filtering scores;
and
each collaborative filtering score of the plurality of collaborative filtering scores is based on the same raw collaborative filtering features, but a different decay factor, as each other of the plurality of collaborative filtering scores.
10. The method of Claim 1 wherein:
the ML score generated for the particular video is one of a plurality of component scores generated by the machine learning engine for the particular video; and
the method further comprises combining plurality of component scores, based on goal information, to produce a composite ML score for the particular video.
11. The method of Claim 1 wherein:
the ML score generated for the particular video is one of a plurality of component scores generated by the machine learning engine for the particular video; and

the method further comprises alternating which component scores, of the plurality of component scores, are used as the basis for selecting which videos to recommend to the particular user.

12. A method comprising:
 - generating a plurality of machine-learning (ML) scores by feeding a corresponding input feed to a machine learning engine for each video in a set of candidate videos;
 - wherein the input feed that corresponds to a particular video in the set of candidate videos includes a plurality of parameter values;
 - selecting one or more videos, from the set of candidate videos, to recommend to a particular user based, at least in part, on the ML scores;
 - wherein the one or more videos selected for recommendation to the particular user includes the particular video;
 - for the particular video, determining a recommendation reason, from a plurality of possible recommendation reasons, based on how the machine learning engine weighted the plurality of parameter values when generating the ML score for the particular video;
 - causing an indication of the recommendation reason to be presented to the particular user, in association with a recommendation of the particular video;
 - wherein the method is performed by one or more computing devices.
13. A method comprising:
 - generating a plurality of machine-learning (ML) scores by feeding a corresponding input feed to a machine learning engine for each video in a set of candidate videos;
 - wherein the input feed that corresponds to a particular video in the set of candidate videos includes a plurality of parameter values;
 - wherein the plurality of parameter values includes a first set of parameter values and a second set of parameter values;
 - wherein the first set of parameter values are generated based on a model that employs a particular model tuning parameter;
 - wherein the first set of parameter values includes, for each model tuning parameter value of a plurality of model tuning parameter values for the particular model tuning

- parameter, at least one parameter value that is based on the model tuning parameter value;
- wherein the second set of parameter values includes one or more parameter values that are independent of the model tuning parameter;
- wherein, when generating the ML score for the particular video, the machine learning engine determines how much weight to give to each parameter value in the first set of parameter values based, at least in part, on the parameter values in the second set of parameter values; and
- selecting one or more videos, from the set of candidate videos, to recommend to a particular user based, at least in part, on the ML scores;
- wherein the method is performed by one or more computing devices.
14. The method of Claim 13 wherein the particular model tuning parameter is a decay factor used by the model.
15. The method of Claim 13 wherein the particular model tuning parameter is an odds-ratio cut off used by the model.
16. The method of Claim 13 wherein the particular model tuning parameter is a normalization factor used by the model.
17. The method of Claim 13 wherein:
- the model uses a plurality of model tuning parameters; and
- each parameter value in the first set of parameter values is based on a distinct combination of model tuning parameter values for the plurality of model tuning parameters.
18. The method of Claim 1 further comprising:
- building a bloomfilter based on behavior data that indicates videos with which users have recently interacted; and
- generating training input for the machine learning system by using the bloomfilter to filter out collaborative filtering features and content-based filtering features that do not relate to the videos with which users have recently interacted.
19. The method of Claim 1 further comprising performing an asymmetric join of the content-based filtering features with the collaborative filtering features such that content-based filtering features are only joined with collaborative filtering features that were generated within a threshold period of time.

20. The method of Claim 1 further comprising performing constrained exploration by organizing candidate videos into pools based, at least in part, on the ML scores, and selecting videos to recommend from the pools using a multi-armed bandit technique.
21. The method of Claim 20 wherein the multi-armed bandit technique involves an epsilon-greedy strategy.
22. One or more non-transitory computer-readable media storing instructions which, when executed by one or more processors, cause performance of the method recited in any one of Claims 1-21.
23. A system, comprising one or more computing devices, configured to cause performance of the method recited in any one of Claims 1-21.

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one or more raw collaborative filtering features;
a collaborative filtering score that was generated based on the one or more raw collaborative filtering features;
one or more raw content-based filtering features; and
a content-based filtering score that was generated based on the one or more raw content-based filtering features;
when generating the ML score for the particular video, the machine learning engine determining weights to give the collaborative filtering score and the content-based filtering score based, at least in part, on the one or more raw collaborative filtering features and the one or more raw content-based filtering features;
selecting one or more videos, from the set of candidate videos, to recommend to a particular user based, at least in part, on the ML scores.
2. The method of Claim 1 wherein:
the input feed for the particular video includes video-pair-centric metrics for a video pair that includes the particular video and a compared video;
the one or more raw collaborative filtering features include collaborative filtering metrics for the video pair; and
the one or more raw content-based filtering features include content-based filtering metrics for the video pair.
3. The method of Claim 2 wherein the collaborative filtering metrics of the video pair are only updated in response to detecting a new indication of user interest with one or more of the videos in the video pair.

4. The method of Claim 2 wherein the content-based filtering metrics of the video pair are only updated in response to detecting a new change in video metadata for one or more of the videos in the video pair.
5. The method of Claim 2 wherein:
the video-pair-centric metrics of the video pair includes a particular set of metrics; and
the particular set of metrics is maintained for the video pair if and only if the video pair satisfies a particular pairing test.
6. The method of Claim 5 wherein the particular set of metrics includes all of the video-pair-centric metrics.
7. The method of Claim 5 wherein the particular set of metrics includes only one of:
the collaborative filtering metrics for the video pair; and
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8. The method of Claim 7 further comprising using a second pairing test, that is different than the pair test, to determine whether to maintain, for the video pair, the other of:
the collaborative filtering metrics for the video pair; and
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9. The method of Claim 1 wherein:
the input feed for the particular video includes a plurality of collaborative filtering scores;
and
each collaborative filtering score of the plurality of collaborative filtering scores is based on the same raw collaborative filtering features, but a different decay factor, as each other of the plurality of collaborative filtering scores.
10. The method of Claim 1 wherein:
the ML score generated for the particular video is one of a plurality of component scores generated by the machine learning engine for the particular video; and

the method further comprises combining plurality of component scores, based on goal information, to produce a composite ML score for the particular video.

11. The method of Claim 1 wherein:

the ML score generated for the particular video is one of a plurality of component scores generated by the machine learning engine for the particular video; and
the method further comprises alternating which component scores, of the plurality of component scores, are used as the basis for selecting which videos to recommend to the particular user.

12. A method comprising:

generating a plurality of machine-learning (ML) scores by feeding a corresponding input feed to a machine learning engine for each video in a set of candidate videos;
wherein the input feed that corresponds to a particular video in the set of candidate videos includes a plurality of parameter values;
selecting one or more videos, from the set of candidate videos, to recommend to a particular user based, at least in part, on the ML scores;
wherein the one or more videos selected for recommendation to the particular user includes the particular video;
for the particular video, determining a recommendation reason, from a plurality of possible recommendation reasons, based on how the machine learning engine weighted the plurality of parameter values when generating the ML score for the particular video;
causing an indication of the recommendation reason to be presented to the particular user, in association with a recommendation of the particular video.

13. A method comprising:

generating a plurality of machine-learning (ML) scores by feeding a corresponding input feed to a machine learning engine for each video in a set of candidate videos;
wherein the input feed that corresponds to a particular video in the set of candidate videos includes a plurality of parameter values;

wherein the plurality of parameter values includes a first set of parameter values and a second set of parameter values;

wherein the first set of parameter values are generated based on a model that employs a particular model tuning parameter;

wherein the first set of parameter values includes, for each model tuning parameter value of a plurality of model tuning parameter values for the particular model tuning parameter, at least one parameter value that is based on the model tuning parameter value;

wherein the second set of parameter values includes one or more parameter values that are independent of the model tuning parameter;

wherein, when generating the ML score for the particular video, the machine learning engine determines how much weight to give to each parameter value in the first set of parameter values based, at least in part, on the parameter values in the second set of parameter values; and

selecting one or more videos, from the set of candidate videos, to recommend to a particular user based, at least in part, on the ML scores.

14. The method of Claim 13 wherein the particular model tuning parameter is a decay factor used by the model.
15. The method of Claim 13 wherein the particular model tuning parameter is an odds-ratio cut off used by the model.
16. The method of Claim 13 wherein the particular model tuning parameter is a normalization factor used by the model.
17. The method of Claim 13 wherein:
the model uses a plurality of model tuning parameters; and
each parameter value in the first set of parameter values is based on a distinct combination of model tuning parameter values for the plurality of model tuning parameters.

18. The method of Claim 1 further comprising:
building a bloomfilter based on behavior data that indicates videos with which users have recently interacted; and
generating training input for the machine learning system by using the bloomfilter to filter out collaborative filtering features and content-based filtering features that do not relate to the videos with which users have recently interacted.
19. The method of Claim 1 further comprising performing an asymmetric join of the content-based filtering features with the collaborative filtering features such that content-based filtering features are only joined with collaborative filtering features that were generated within a threshold period of time.
20. The method of Claim 1 further comprising performing constrained exploration by organizing candidate videos into pools based, at least in part, on the ML scores, and selecting videos to recommend from the pools using a multi-armed bandit technique.
21. The method of Claim 20 wherein the multi-armed bandit technique involves an epsilon-greedy strategy.
22. One or more computer-readable media carrying instructions which, when executed by one or more processors, cause performance of the method recited in any one of Claims 1-21.
23. A system, comprising one or more computing devices, configured to cause performance of the method recited in any one of Claims 1-21.