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Supplemental information

Using biological constraints to improve

prediction in precision oncology

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Supplemental figures and legends

Figure S1. An example of the coherent feed-forward loops (FFLs) used in predicting bladder cancer progression, related to STAR Methods. Here, MYC is a transcription factor repressing a downstream target gene (CD164) directly and indirectly by activating a miRNA hub (has-miR-346).

Mechanistic (37 FFLs) vs agnostic (different N of features/pairs) performance at predicting bladder cancer progression in the testing data

Figure S2. The testing performance of mechanistic and agnostic models at predicting bladder cancer progression, related to Figure 2. Models were trained on 1000 bootstraps of the training data (not shown) and evaluated on the testing data using the AUC as evaluation metric. Mechanistic models were based on the feed-forward loops mechanism (37 unique pairs). Agnostic models were built using either the top differentially expressed genes (top 74, 100, 200, or 500 DEGs) or the corresponding pairwise comparisons (37, 50, 100, or 250 pairs). k-TSPs: k-top scoring pairs; RF: random forest; SVM: support vector machine; XGB: extreme gradient boosting; DEGs: differentially expressed genes; AUC: Area Under the ROC Curve.

Figure S3. Comparing the testing performance of the mechanistic models and classifiers trained on different numbers of randomly selected genes at predicting bladder cancer progression, related to Figure 2. Models were trained on 1000 bootstraps of the training data (not shown) and evaluated on the testing data using the AUC as evaluation metric. Mechanistic models were based on the feed-forward loops mechanism (37 unique pairs). Random genes models were trained using randomly selected genes (74, 100, 200, or 500 genes). k-TSPs: K-top scoring pairs; RF: random forest; SVM: support vector machine; XGB: extreme gradient boosting; DEGs: differentially expressed genes; AUC: Area Under the ROC Curve.

echanistic (241 pairs) vs agnostic (different N of features/pairs) performance at predicting the response to neoadjuvant chemotherapy in the testing dat

Figure S4. The testing performance of the mechanistic and agnostic models at predicting triple-negative breast cancer response to neoadjuvant chemotherapy, related to Figure 4. Models were trained on 1000 bootstraps of the training data (not shown) and evaluated on the testing data using the AUC as evaluation metric. Mechanistic models were based on the NOTCH-MYC mechanism (241 unique pairs). Agnostic models were built using either the top differentially expressed genes (top 50, 100, 200, or 500 DEGs) or the corresponding pairwise comparisons (25, 50, 100, or 250 pairs). k-TSPs: k-top scoring pairs; RF: random forest; SVM: support vector machine; XGB: extreme gradient boosting; DEGs: differentially expressed genes; TNBC: triple-negative breast cancer; NACT: neoadjuvant chemotherapy; AUC: Area Under the ROC Curve.

Figure S5. Comparing the testing performance of the mechanistic models versus random genes classifiers at predicting triple-negative breast cancer response to neoadjuvant chemotherapy, related to Figure 4. Models were trained on 1000 bootstraps of the training data (not shown) and evaluated on the untouched testing data using the AUC as evaluation metric. Mechanistic models were based on the NOTCH-MYC mechanism (241 unique pairs). Random genes models were trained using different numbers of randomly selected genes (50, 100, 200, or 500 genes). k-TSPs: K-top scoring pairs; RF: random forest; SVM: support vector machine; XGB: extreme gradient boosting; DEGs: differentially expressed genes; TNBC: triple-negative breast cancer; NACT: neoadjuvant chemotherapy; AUC: Area Under the ROC Curve.

Mechanistic (50 pairs) vs agnostic (different N of features/pairs) performance at predicting prostate cancer metastasis in the testing data

Figure S6. The testing performance of the mechanistic and agnostic models at predicting prostate cancer metastatic progression, related to Figure 6. Models were trained on 1000 bootstraps of the training data (not shown) and evaluated on the untouched testing data using the AUC as evaluation metric. Mechanistic models were based on the cellular adhesion and $O₂$ response mechanism (50 pairs). Agnostic models were built using either the top differentially expressed genes (top 50, 100, 200, or 500 DEGs) or the corresponding pairwise comparisons (25, 50, 100, or 250 pairs). k-TSPs: K-top scoring pairs; RF: random forest; SVM: support vector machine; XGB: extreme gradient boosting; DEGs: differentially expressed genes; AUC: Area Under the ROC Curve.

Figure S7. Comparing the testing performance of the mechanistic models versus random genes classifiers at predicting prostate cancer metastatic progression, related to Figure 6. Models were trained on 1000 bootstraps of the training data (not shown) and evaluated on the testing data using the AUC as evaluation metric. Mechanistic models were based on the cellular adhesion and O² response mechanism (50 pairs). Random genes models were trained using different numbers of randomly selected genes (50, 100, 200, or 500 genes). K-TSPs: K-top scoring pairs; RF: random forest; SVM: support vector machine; XGB: extreme gradient boosting; DEGs: differentially expressed genes; AUC: Area Under the ROC Curve.

Supplemental Tables 2,4, and 6

Table S2. The average performance of the agnostic and mechanistic models at predicting bladder cancer progression in the cross-study validation design, related to STAR Methods. The analysis had five iterations and in each, four studies were used for training while the fifth was used for testing. This table depicts the average training and testing performance at predicting the progression to muscle-invasive stages across the five iterations. Agnostic models were trained using either gene expression values (agnostic genes) or their pairwise comparisons (agnostic Pairs). Mechanistic models were based on the FFLs mechanism.

a Note that for the K-TSPs algorithm, only pairs can be used for classification.

K-TSPs: K-Top Scoring Pairs; RF: Random Forest; SVM: Support Vector Machine; XGB: Extreme Gradient Boosting; AUC: Area Under the ROC Curve; MCC: Matthews Correlation Coefficient.

Table S4. The average performance of the agnostic and mechanistic models at predicting the response to neoadjuvant chemotherapy in patients with triple-negative breast cancer, related to STAR Methods. Here, the analysis had seven iterations and in each, six of the seven studies were used for training while the seventh was used for testing. The table shows the average training and testing performance at predicting the response to NACT across these seven iterations. Agnostic models were trained using either gene expression values (Agnostic genes) or their pairwise comparisons (Agnostic Pairs). Mechanistic models were based on the NOTCH-MYC mechanism.

 \overline{a} Note that for the K-TSPs algorithm, only pairs can be used for classification.

K-TSPs: K-Top Scoring Pairs; RF: Random Forest; SVM: Support Vector Machine; XGB: Extreme Gradient Boosting; AUC: Area Under the ROC Curve;

MCC: Matthews Correlation Coefficient.

Table S6. The average performance of the agnostic and mechanistic models at predicting prostate cancer metastatic progression, related to STAR Methods. The analysis included seven iterations and in each, six of the seven studies were used for training while the seventh was used for testing. The table shows the average training and testing performance at predicting metastatic events across these seven iterations. Agnostic models were trained using either individual gene expression values (Agnostic genes) or their corresponding pairwise comparisons (Agnostic Pairs). Mechanistic models were based on the cellular adhesion and $O₂$ response mechanism.

 \overline{a} Note that for the K-TSPs algorithm, only pairs can be used for classification.

K-TSPs: K-Top Scoring Pairs; RF: Random Forest; SVM: Support Vector Machine; XGB: Extreme Gradient Boosting; AUC: Area Under the ROC Curve;

MCC: Matthews Correlation Coefficient.