

Prognostic Models in Oncology: From Feature Selection to Web Apps

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UT Health San Antonio – December 5, 2023

Collaboration



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Long, J.P. and Shen, Y., 2023. Detection method has independent prognostic significance in the PLCO lung screening trial. *Scientific reports*, 13(1), p.13382.

Sherise D Ferguson, Tiffany R Hodges, Nazanin K Majd, Kristin Alfaro-Munoz, Wajd N Al-Holou, Dima Suki, John F de Groot, Gregory N Fuller, Lee Xue, Miao Li, Carmen Jacobs, Ganesh Rao, Rivka R Colen, Joanne Xiu, Roel Verhaak, David Spetzler, Mustafa Khasraw, Raymond Sawaya, **James P Long**, Amy B Heimberger. A validated integrated clinical and molecular glioblastoma long-term survival-predictive nomogram. *Neuro-oncology advances*, 3(1), p.vdaa146.

Outline

Prognostic Models

Feature: Cancer Detection Method

Models and Algorithms: Random Survival Forests

Web Apps for Sharing Models

Outline

Prognostic Models

Feature: Cancer Detection Method

Models and Algorithms: Random Survival Forests

Web Apps for Sharing Models

What are Prognostic Models?

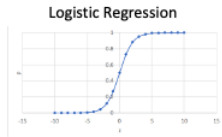
Variables / Features / Predictors

Model / Algorithm

Predictions

Clinical

- Age
- Disease Subtype
- Prior Treatments

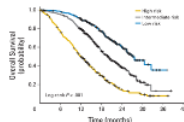


Responder
VS.
Non-Responder

Genomic

- PTEN Mutation
- RB1 Mutation
- KRAS Expression

Random Forests



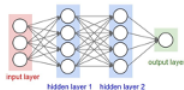
Legend for OS

| Time (months) | High risk | Intermediate risk | Low risk |
|---------------|-----------|-------------------|----------|
| 0 | 1.00 | 1.00 | 1.00 |
| 10 | 0.85 | 0.95 | 1.00 |
| 20 | 0.65 | 0.85 | 0.95 |
| 30 | 0.45 | 0.75 | 0.85 |
| 40 | 0.35 | 0.65 | 0.75 |

Imaging

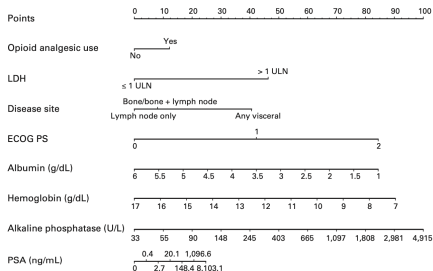
- T1 Flair
- Necrosis Volume

Deep Neural Network

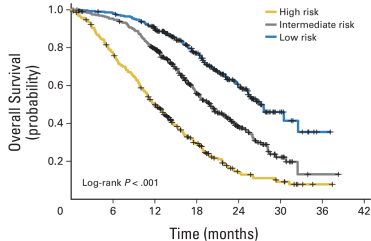


Example 1: mCRPC

- Halabi et al. [2014] developed prognostic model for predicting time from metastasis to death in metastatic castrate resistant prostate cancer (mCRPC)
- Model score stratifies patients into risk groups [Halabi et al., 2023]



D



| No. at risk | 290 | 281 | 243 | 144 | 71 | 13 | 1 |
|-------------------|-----|-----|-----|-----|----|----|---|
| Low risk | 290 | 281 | 243 | 144 | 71 | 13 | 1 |
| Intermediate risk | 326 | 307 | 243 | 130 | 52 | 13 | 1 |
| High risk | 284 | 215 | 137 | 59 | 16 | 9 | 1 |

Example 2: Lung Cancer

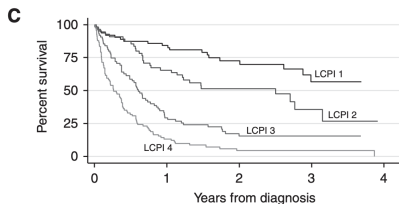
- Alexander et al. [2017] developed Lung Cancer Prognostic Index (LCPI) for predicting time from diagnosis to death in Lung Cancer

Table 3. Weighted scores for predictive model for overall survival in newly diagnosed non-small-cell lung cancer

| | LCPI points | m-LCPI |
|----------------------------------|-------------|--------------|
| Stage group | | |
| I | 0 | 0 |
| II | 2 | 2 |
| IIIA | 5 | 4 |
| IIIB | 7 | 6 |
| IV | 9 | 8 |
| NSCLC NOS | 3 | 3 |
| No proven actionable mutation* | 3 | 3 |
| ECOG performance status ≥ 2 | 3 | Excluded |
| Ever smoker | 2 | 2 |
| Respiratory comorbidity | 2 | 2 |
| Weight loss $> 10\%$ | 2 | Excluded |
| Male sex | 1 | 1 |
| Age group 50 or less | | |
| ≤ 50 years | 0 | 0 |
| 51–70 | 1 | 1 |
| 71–90 | 2 | 2 |
| ≥ 91 years | 3 | 3 |
| LCPI Group | LCPI score | m-LCPI score |
| LCPI 1 | ≤ 9 | ≤ 8 |
| LCPI 2 | 10–13 | 9–11 |
| LCPI 3 | 14–16 | 12–14 |
| LCPI 4 | ≥ 17 | ≥ 15 |

Abbreviations: ALK = anaplastic lymphoma kinase; ECOG = Eastern Cooperative Oncology Group; EGFR = epidermal growth factor receptor; LCPI = Lung Cancer Prognostic Index; m-LCPI = modified lung cancer prognostic index; NOS = not otherwise specified; NSCLC = non-small-cell lung cancer.

*Includes EGFR/ALK negative, KRAS positive, mutation not tested.



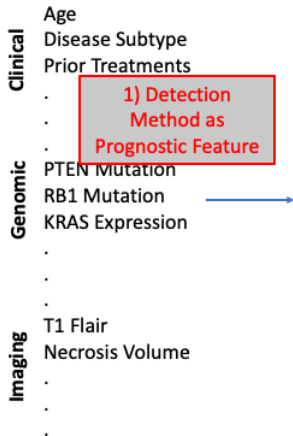
| | | | | | | |
|----------------|----|----|----|----|---|---|
| Number at risk | | | | | | |
| LCPI 1 (≤9) | 63 | 54 | 33 | 22 | 4 | 0 |
| LCPI 2 (10–13) | 55 | 37 | 21 | 13 | 3 | 0 |
| LCPI 3 (14–16) | 75 | 29 | 14 | 6 | 4 | 0 |
| LCPI 4 (≥17) | 91 | 15 | 5 | 2 | 2 | 0 |

Today's Talk

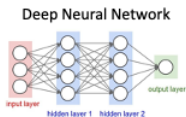
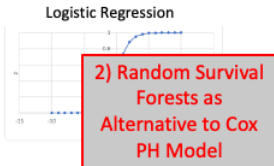
Variables / Features / Predictors

Model / Algorithm

Predictions

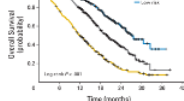


1) Detection Method as Prognostic Feature



Responder
vs.
Non-Responder

3) Sharing Models with Shiny Web Apps



| | | | | | | | |
|---------------|-----|-----|-----|-----|----|----|---|
| No. at risk | 200 | 201 | 202 | 148 | 11 | 13 | 1 |
| Responder | 200 | 201 | 202 | 148 | 11 | 13 | 1 |
| Non-Responder | 200 | 201 | 202 | 148 | 11 | 13 | 1 |

Outline

Prognostic Models

Feature: Cancer Detection Method

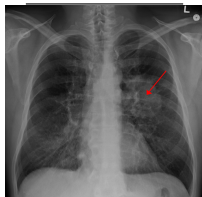
Models and Algorithms: Random Survival Forests

Web Apps for Sharing Models

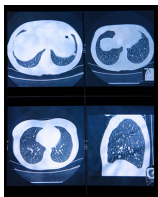
Cancer Screening

- Cancer screening has the potential to detect tumors early, prior to clinical symptoms.
- Cancers diagnosed at an early stage (I or II) have better prognosis than those diagnosed at a late stage (III or IV)

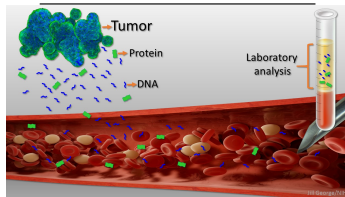
Chest X-Ray



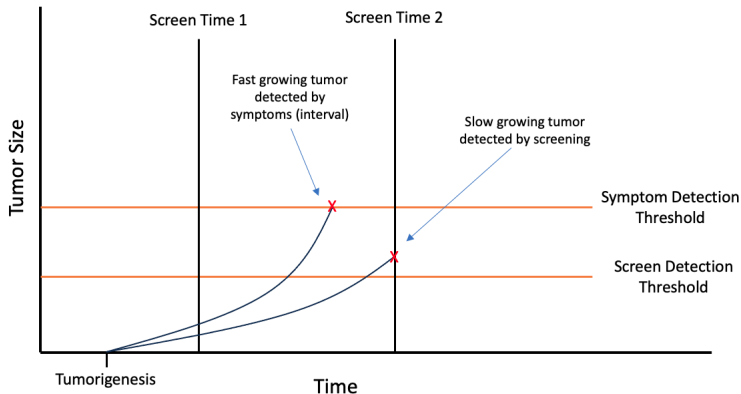
Low-Dose CT



Circulating Biomarkers



Detection Method and Tumor Growth Rate



Screen detected tumors are (on average) slower growing than interval detected tumors. [Albert et al., 1978, Morrison, 1992, Kramer et al., 2021]

Detection Method and Prognostic Significance

- Detection Method = Screen or Interval
- Expect screen detected tumors to have better prognosis:
Screen detection → earlier stage at diagnosis → better prognosis
- Screen detected tumors tend to be slower growing than interval detected tumors.
 - Tumor growth rate is rarely known, not used in prognostic models.
 - Detection method may be a proxy for tumor growth rate.

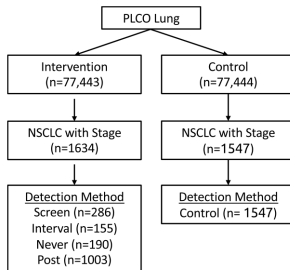
Existing Literature and Hypothesis

- Joensuu et al. [2004] found lower risk of distant recurrence in Screen detected breast cancers relative to interval detected.
- Shen et al. [2005] found better survival in screen-detected breast cancer
- Mook et al. [2011] found screen detected breast tumors have better survival
- Most existing work studying prognostic value of detection method focused on breast cancer and mammograms

Hypothesis: Detection Method has independent prognostic significance in predicting survival time in patients diagnosed with lung cancer.

PLCO Screening Trial

- We obtained data from the PLCO Cancer Screening Trial [Andriole et al., 2005]
- PLCO assessed efficacy of screening in 4 cancer types
- The Lung cohort of PLCO compared 4 annual chest X-rays to standard of care



Detection Method:

- Screen = Detected at annual X-ray screening
- Interval = Detected between annual screenings
- Never = Detected in patient who did not attend screenings
- Post = Detected after screening period ended
- Control = Detected in control group.

PLCO Screening Trial

- Performed two analyses:
 - 4-year cohort: Patients diagnosed lung cancer within 4 years after randomization
 - Extended cohort: All patients diagnosed with NSCLC with Stage information
- Grouped Never and Post detected tumors into category Other
 - Detection Method = {Screen,Interval,Other,Control}

Cohort Summary

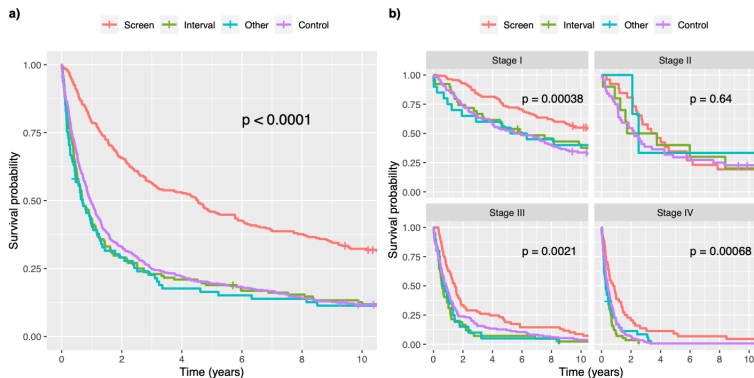
Table 1. Characteristics of lung cancers detected in PLCO.

| Characteristic | Screen, N = 279 | Interval, N = 148 | Other, N = 81 | Control, N = 426 | p-value |
|---------------------|-----------------|-------------------|---------------|------------------|---------|
| Stage | | | | | <0.001 |
| Stage I | 140 (50%) | 39 (26%) | 20 (25%) | 101 (24%) | |
| Stage II | 26 (9.3%) | 10 (6.8%) | 3 (3.7%) | 44 (10%) | |
| Stage III | 69 (25%) | 42 (28%) | 20 (25%) | 134 (31%) | |
| Stage IV | 44 (16%) | 57 (39%) | 38 (47%) | 147 (35%) | |
| Age | | | | | 0.5 |
| <=59 | 58 (21%) | 37 (25%) | 11 (14%) | 83 (19%) | |
| 60-64 | 67 (24%) | 35 (24%) | 24 (30%) | 125 (29%) | |
| 65-69 | 98 (35%) | 46 (31%) | 28 (35%) | 126 (30%) | |
| >=70 | 56 (20%) | 30 (20%) | 18 (22%) | 92 (22%) | |
| Sex | | | | | 0.5 |
| Female | 113 (41%) | 59 (40%) | 36 (44%) | 157 (37%) | |
| Male | 166 (59%) | 89 (60%) | 45 (56%) | 269 (63%) | |
| Smoked | | | | | <0.001 |
| No | 23 (8.2%) | 8 (5.4%) | 5 (6.2%) | 29 (6.8%) | |
| Yes | 256 (92%) | 139 (94%) | 63 (78%) | 377 (88%) | |
| Unknown | 0 (0%) | 1 (0.7%) | 13 (16%) | 20 (4.7%) | |
| Histology | | | | | <0.001 |
| Adenocarcinoma | 134 (48%) | 58 (39%) | 29 (36%) | 189 (44%) | |
| Bronchiolo-alveolar | 33 (12%) | 10 (6.8%) | 2 (2.5%) | 20 (4.7%) | |
| Squamous cell | 59 (21%) | 33 (22%) | 23 (28%) | 109 (26%) | |
| Large cell | 21 (7.5%) | 10 (6.8%) | 3 (3.7%) | 26 (6.1%) | |
| Other NSC | 6 (2.2%) | 4 (2.7%) | 2 (2.5%) | 4 (0.9%) | |
| Carcinoma, NOS | 21 (7.5%) | 28 (19%) | 21 (26%) | 74 (17%) | |
| Other/Unknown | 5 (1.8%) | 5 (3.4%) | 1 (1.2%) | 4 (0.9%) | |

n (%)

Fisher's Exact Test for Count Data with simulated p-value(based on 2000 replicates)

Survival by Detection Method



- Left: Screen detected tumors how much longer survival times than other types.
- Right: Difference remains significant after controlling for stage.
 - This suggests Detection Method has independent prognostic significance (perhaps because proxy for tumor growth rate).

LCPI [Alexander et al., 2017]

1. Used a Cox Proportional Hazards model (Cox PH) to identify important predictors of survival for NSCLC in Australian cohort.
2. Points assigned to values of variable (Stage II = 2 points, Stage IV = 9 points) based on hazard ratios in Cox model.
3. Cutoffs chosen based on total points to classify patients into LCPI I through IV.
4. Kaplan Meier survival curves compared for LCPI I - IV on validation sets.

Step 1

Table 2. Predictors of survival in the derivation cohort by multivariate Cox model

| | LCPI | | | |
|--|------|--------|------------|----------------------|
| | HR | Log HR | 95% CI | P-value ^a |
| Stage group | | | | |
| II | 1.0 | 0.00 | | |
| IIIA | 1.57 | 0.45 | 0.96-2.58 | 0.09 |
| IIIB | 3.06 | 1.12 | 2.05-4.57 | <0.01 |
| IV | 4.45 | 1.49 | 2.91-6.84 | <0.01 |
| IV | 7.98 | 2.08 | 5.55-11.52 | <0.01 |
| NSCLC NOS | 1.91 | 0.65 | 1.48-2.65 | <0.01 |
| No proven actionable mutation ^b | 1.91 | 0.65 | 1.31-2.53 | <0.01 |
| ECOG performance status ≥ 2 | 1.78 | 0.57 | 1.40-2.23 | <0.01 |
| Ever Smoker | 1.65 | 0.50 | 1.19-2.35 | <0.01 |
| Respiratory comorbidity | 1.46 | 0.38 | 1.11-1.68 | <0.01 |
| Weight loss $> 10\%$ | 1.42 | 0.35 | 1.13-1.79 | <0.01 |
| Male sex | 1.36 | 0.31 | 1.11-1.68 | 0.01 |
| Age (per 20 years aged > 50) | 1.25 | 0.22 | 1.05-1.50 | <0.01 |

Abbreviations: ALK=anaplastic lymphoma kinase; CI=confidence interval; ECOG=Eastern Cooperative Oncology Group; EGFR=epidermal growth factor receptor; LCPI=Lung Cancer Prognostic Index; NOS=not otherwise specified.

^aP-value for the comparison of overall survival for patients with and without the specified factor, or for stage group.

^bIncludes EGFR/ALK negative, KRAS positive, mutation not tested.

Step 2 + 3

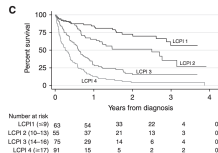
Table 3. Weighted scores for predictive model for overall survival in newly diagnosed non-small-cell lung cancer

| | LCPI points | m-LCPI |
|--|-------------|--------------|
| Stage group | | |
| II | 0 | 0 |
| IIIA | 2 | 2 |
| IIIB | 5 | 5 |
| IV | 9 | 8 |
| NSCLC NOS | 3 | 3 |
| No proven actionable mutation ^a | 3 | 3 |
| ECOG performance status ≥ 2 | 3 | Excluded |
| Ever smoker | 2 | 2 |
| Respiratory comorbidity | 2 | 2 |
| Weight loss $> 10\%$ | 2 | Excluded |
| Male sex | 1 | 1 |
| Age group 50 or less | | |
| <50 years | 0 | 0 |
| 51-70 | 1 | 1 |
| 71-90 | 2 | 2 |
| ≥ 91 years | 3 | 3 |
| LCPI Group | LCPI score | m-LCPI score |
| LCPI 1 | ≤ 9 | ≤ 8 |
| LCPI 2 | 10-13 | 9-11 |
| LCPI 3 | 14-16 | 12-14 |
| LCPI 4 | ≥ 17 | ≥ 15 |

Abbreviations: ALK=anaplastic lymphoma kinase; ECOG=Eastern Cooperative Oncology Group; EGFR=epidermal growth factor receptor; LCPI=Lung Cancer Prognostic Index; m-LCPI=modified lung cancer prognostic index; NOS=not otherwise specified; NSCLC=non-small-cell lung cancer.

^aIncludes EGFR/ALK negative, KRAS positive, mutation not tested.

Step 4



Testing Hypothesis

1. Identified all significant prognostic variables in LCPI which were also available in PLCO data set.
2. Added Detection Method variable to this set.
3. Fit a Cox Proportional Hazards model on data (following Alexander et al. [2017]).

Cox PH Model Summary

| Characteristic | log(HR) | 95% CI | p-value |
|---------------------|---------|--------------|---------|
| Detection | | | |
| Screen | — | — | |
| Interval | 0.61 | 0.39, 0.83 | <0.001 |
| Other | 0.46 | 0.19, 0.74 | 0.001 |
| Control | 0.43 | 0.26, 0.60 | <0.001 |
| Stage | | | |
| Stage I | — | — | |
| Stage II | 0.50 | 0.24, 0.77 | <0.001 |
| Stage III | 1.3 | 1.1, 1.5 | <0.001 |
| Stage IV | 2.0 | 1.8, 2.3 | <0.001 |
| Age | | | |
| <=59 | — | — | |
| 60-64 | 0.28 | 0.07, 0.49 | 0.008 |
| 65-69 | 0.36 | 0.16, 0.57 | <0.001 |
| >=70 | 0.71 | 0.49, 0.93 | <0.001 |
| Sex | | | |
| Female | — | — | |
| Male | 0.17 | 0.02, 0.31 | 0.024 |
| Smoked | | | |
| No | — | — | |
| Yes | 0.35 | 0.06, 0.65 | 0.020 |
| Unknown | 0.37 | -0.10, 0.83 | 0.12 |
| Histology | | | |
| Adenocarcinoma | — | — | |
| Bronchiolo-alveolar | -0.54 | -0.85, -0.23 | <0.001 |
| Squamous cell | 0.13 | -0.05, 0.31 | 0.2 |
| Large cell | -0.22 | -0.51, 0.07 | 0.13 |
| Other NSC | -0.22 | -0.76, 0.32 | 0.4 |
| Carcinoma, NOS | 0.15 | -0.05, 0.35 | 0.14 |
| Other/Unknown | 0.17 | -0.35, 0.70 | 0.5 |

HR = Hazard Ratio, CI = Confidence Interval

- p-values for Detection Method highly significant
- Hazard ratios for Detection Method larger than for several other prognostic variables such as Sex and Histology
- C-Indices:

| | C-Index |
|-----------|---------|
| LCPI | 0.74 |
| PLCO Lung | 0.76 |

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Proportional Hazards (PH) Assumption

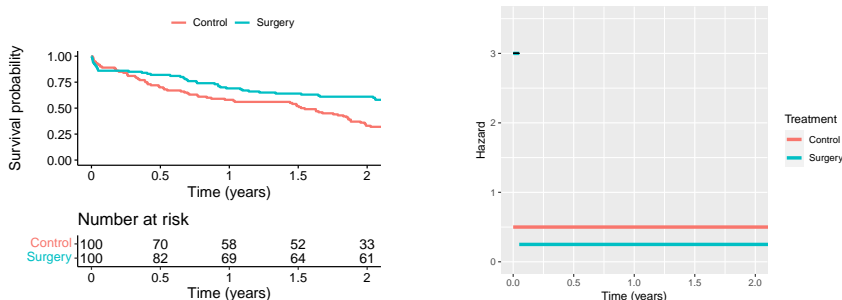
- Hazard at time t = death rate at time t
- Cox Proportional Hazards (Cox PH) model assumes that hazard ratios do not vary with time

$$\widehat{HR} = \frac{\text{Interval Hazard}}{\text{Screen Hazard}} = 1.84$$

- Reality can be much more complicated
 - The hazard ratio may change with time.
 - The hazard ratio may be different for different values of other covariates, e.g. males and females.

Example of Violation of PH Assumption

- Patients randomized to risky surgery or control
- Surgery hazard: Initially high because of surgical complications but lower at later times due to tumor removal
- Control hazard: Constant



$$HR = \frac{\text{Surgery Hazard}}{\text{Control Hazard}} = \begin{cases} 6 & 0 < t < 0.1 \\ 0.5 & t > 0.1 \end{cases}$$

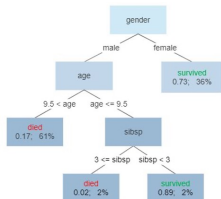
Cox PH Estimated Hazard = 0.57

Consequences of Violations in Model Assumptions

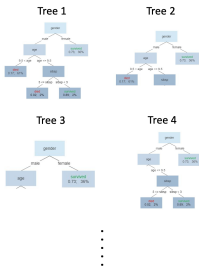
- “All models are wrong, some models are useful.”
 - George E.P. Box
- Severity in violation of PH assumption is important
- Concerns with PLCO Lung Application:
 1. Detection Method may no longer be a significant predictor if a different model is used
 2. Other models may obtain better prediction performance (e.g. C-index)

Random Survival Forests (RSF)

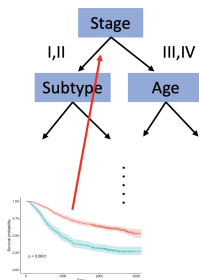
CART (1984)



Random Forest (2001)



RSF (2008)



| | Interpretation | Prediction | Assumptions | Data Size |
|--------|----------------|------------|-------------|-----------|
| Cox PH | ✓ | | | Smaller |
| RSF | | ✓ | ✓ | Larger |

RSF Variable Importance

- Project Goal: Assess importance of Detection Method in Prognostic models
 - CoxPH variable importance usually measured by size of HR and p-values
 - RSF does not directly compute HR or p-values
- RSF Variable Importance
 1. Values of a variable X are permuted among the patients.
 2. Compute C-index using permuted X variable.
 3. $VIMP = \text{C-index with true } X - \text{C-index with permuted } X$.

Results of Random Survival Forests

- Variable Importance (VIMP) Scores:

| | 4-Year Cohort | Extended Cohort |
|-----------|---------------|-----------------|
| Stage | 0.17631 | 0.16060 |
| Detection | 0.01440 | 0.00425 |
| Age | 0.00671 | 0.00601 |
| Histology | 0.00382 | 0.00713 |
| Sex | 0.00085 | 0.00311 |
| Smoked | 0.00064 | -0.00012 |

Detection Method is second most important predictor in 4-year cohort.

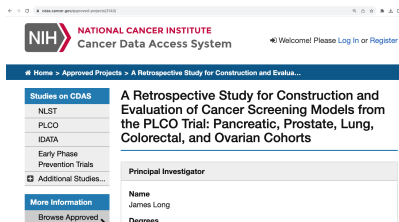
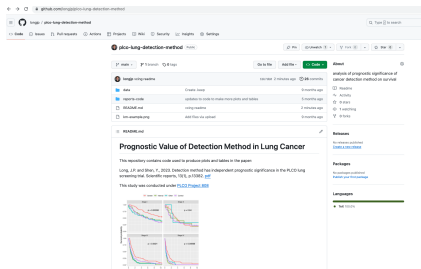
- C-Indices:

| | C-Index |
|--------|---------|
| Cox PH | 0.76 |
| RSF | 0.75 |

Similar between two models.

Reproducible Results

- Project analysis done in RMarkdown
- All code publicly available
- PLCO data may be requested from CDAS



<https://github.com/longjp/plco-lung-detection-method>

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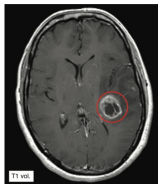
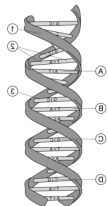
Glioblastoma Multiforme (GBM)

- GBM is the most deadly form of brain cancer
- 5-year survival rate $< 10\%$
- Question: What variables (clinical, imaging, genomic) are predictive of survival? Can we identify long-term survivors?

Project Outline

MD Anderson GBM Patient Cohort

- STS: < 6 months (n=37)
- MTS: 6 months - 5 years (n=22)
- LTS: >5 years (n=21)



Proportions Odds
Ordinal Regression
Model with 5 features

THE CANCER GENOME ATLAS



Validation Cohort



- Considered publishing model as nomogram in paper
 - These can be difficult to use / inaccessible to patients / caregivers

Shiny Web App

← → ↻ biostatistics.mdanderson.org/shinyapps/GBM_Predict/ 🔍 📄 ★ ⚙️ ⬇️ 🗑️

GBM Survival Prediction, PID-1039 v1.0

Predictions

About

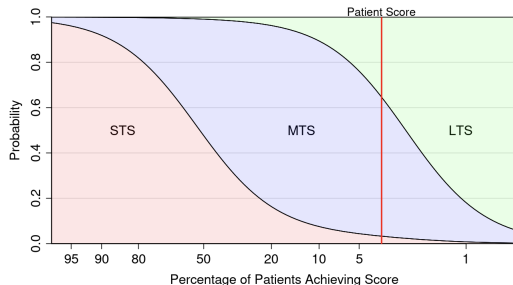
Age: 25 31 37 43 49 55 61 67 73 79 85

KPS: 40 50 60 70 80 90 100

IDH1
☐ Unmutated ☒ Mutated

PTEN
☒ Unmutated ☐ Mutated

TP53
☐ Unmutated ☒ Mutated



https://biostatistics.mdanderson.org/shinyapps/GBM_Predict/

Reproducible Research

Neuro-Oncology Advances

3(1), 1–10, 2021 | doi:10.1093/oaajnl/vdaa146 | Advance Access date 31 October 2020

A validated integrated clinical and molecular glioblastoma long-term survival-predictive nomogram

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The screenshot shows the GitHub repository page for `longjp/GBMpredict`. The repository is under the `master` branch and contains 1 branch and 0 tags. The file list includes:

- `longjp_voting_nomogram` (v4.0.1.1, Oct 10, 2020, 3 years ago)
- `1-clean_hpa.R` (voting analysis code, 3 years ago)
- `1-net_build_model.Rmd` (voting analysis code, 3 years ago)
- `2-validate_model.Rmd` (voting analysis code, 3 years ago)
- `README.md` (voting readme, 3 years ago)
- `nomogram.png` (updated readme, 3 years ago)

The `README.md` file is selected, showing the following content:

Survival Prediction for GBM

Code for building a clinical and genomic predictive model (nomogram) for GBM survival. The resulting nomogram is available here: https://horststatistik.mcgill.ca/longjp/GBM_Predict/

This repository contains data cleaning, model construction, and validation code only, not the web-based nomogram itself. Due to data confidentiality issues, MD Anderson cohort data is not publicly available through this repository. As a result, the code in this repository cannot be executed. For access to the MD Anderson cohort data, please contact Dr_Amy_Heimberger.

Citation and Contact

On the right side of the repository page, there are sections for **About**, **Releases**, **Packages**, and **Languages**.

<https://github.com/longjp/GBMpredict>

Discussion

- Detection Method should be recorded in clinical trial data bases / cancer registries and considered as variable when constructing prognostic models.
- Modern machine learning / AI tools should be considered when constructing prognostic models. But they are not necessarily superior to existing methods on given data set. Comparison of new tool with existing methods is critical.
- Prognostic models can be deployed as web applications to facilitate / accelerate use by clinicians, patients, and caregivers

Thank you. Questions?

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