LineUp

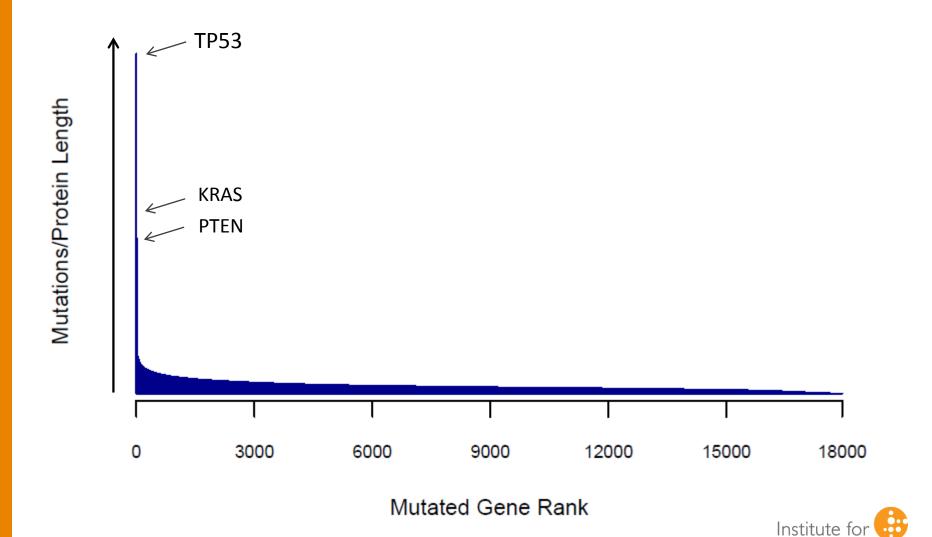
Identifying Deleterious Mutations Using Protein Domain Alignment

Brady Bernard Shmulevich Group



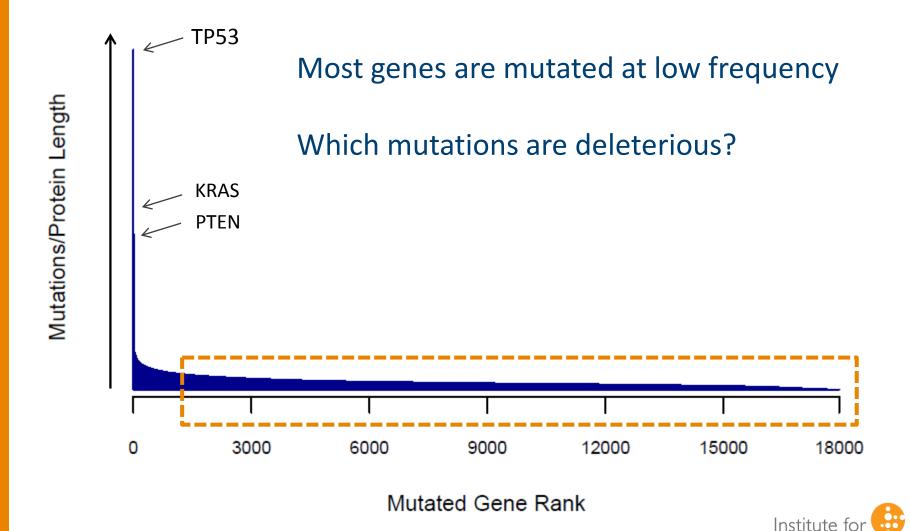


Normalized mutation frequencies Twenty tumor types

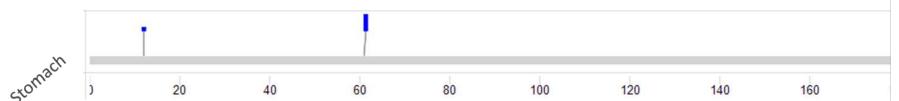


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Normalized mutation frequencies Twenty tumor types

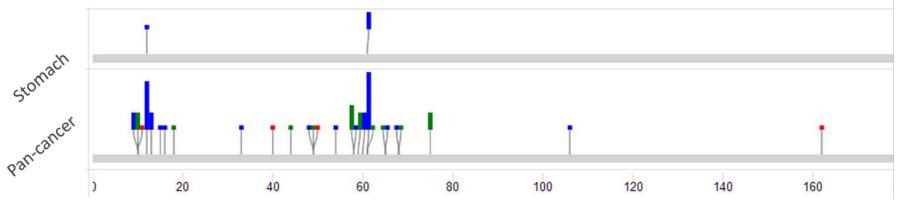


Example protein mutation spectrum



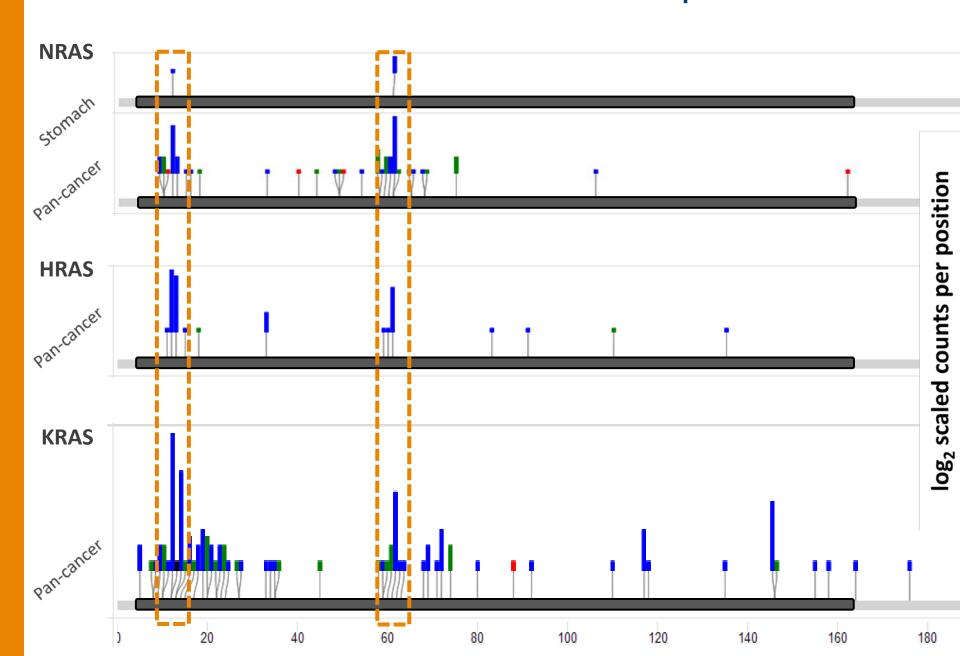


Pan-cancer mutation spectrum





Pan-cancer Ras domain mutation spectra



Ras domain structure alignment

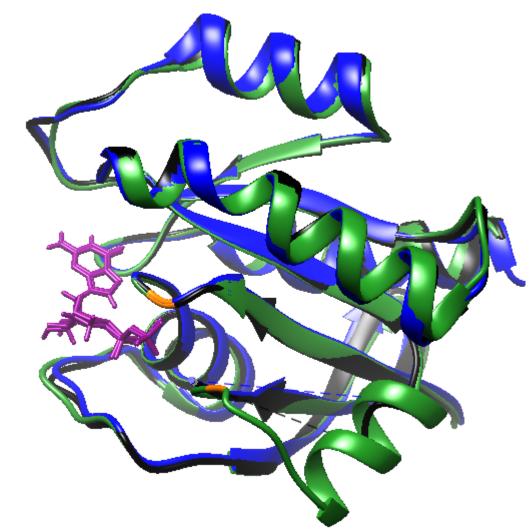
KRAS

NRAS

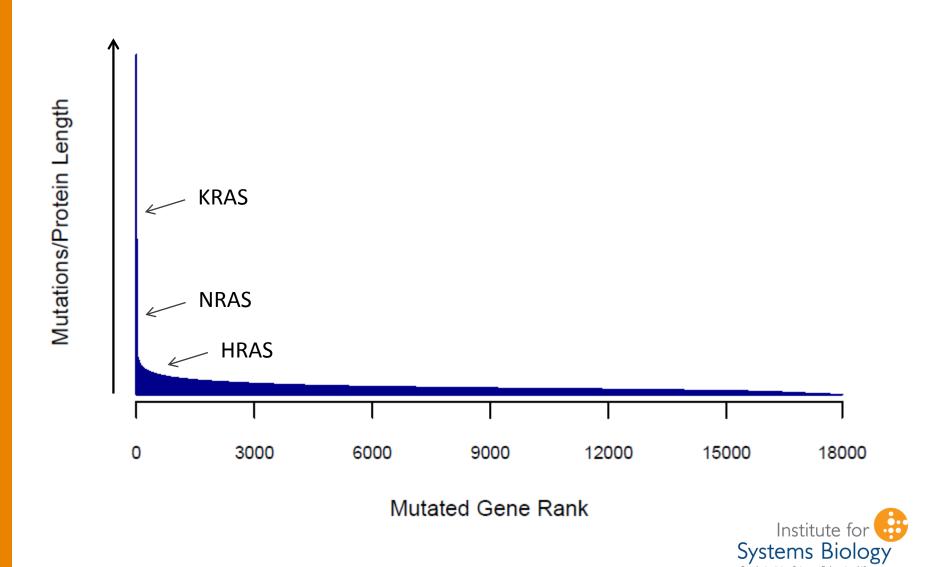
HRAS

GDP

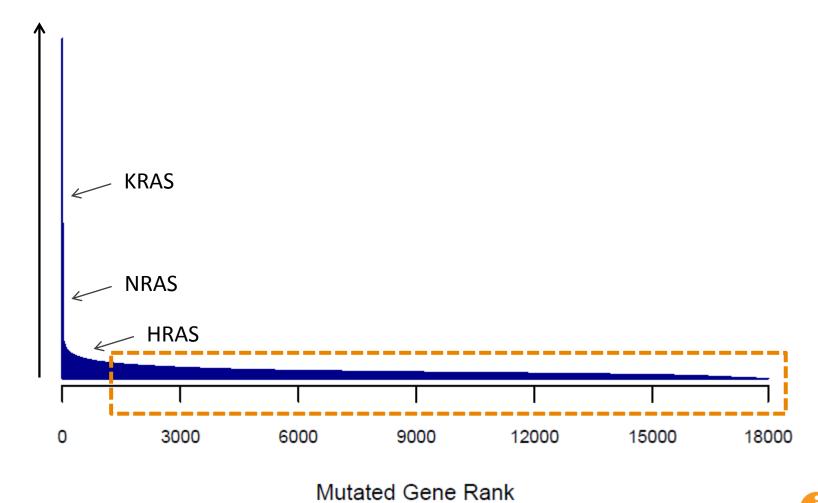
Hotspots





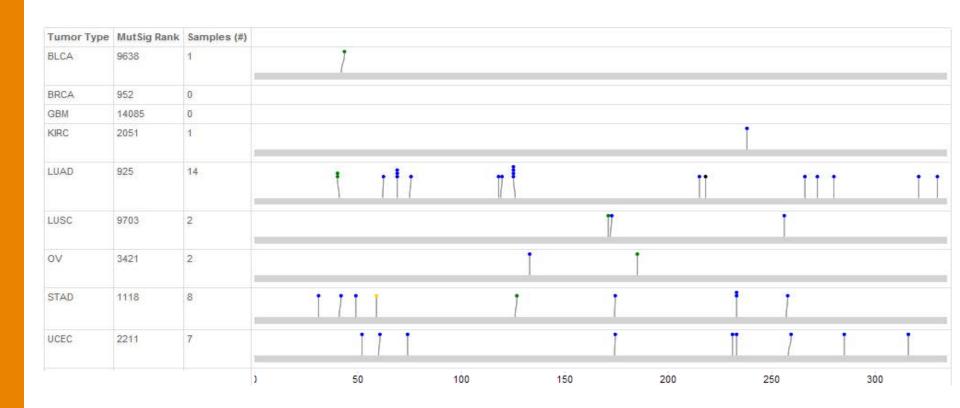


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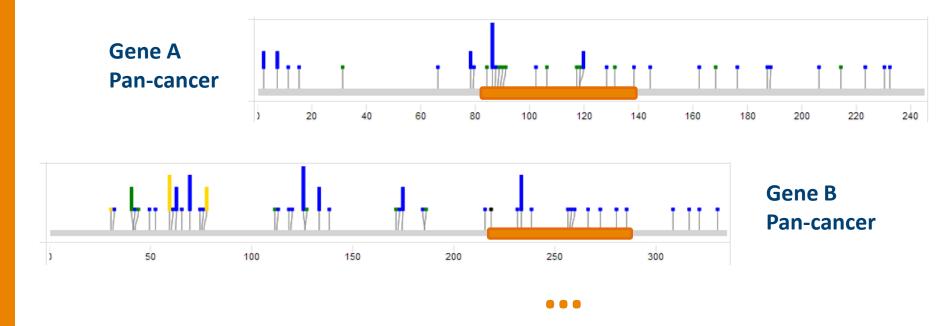
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Typical pan-cancer mutation spectrum





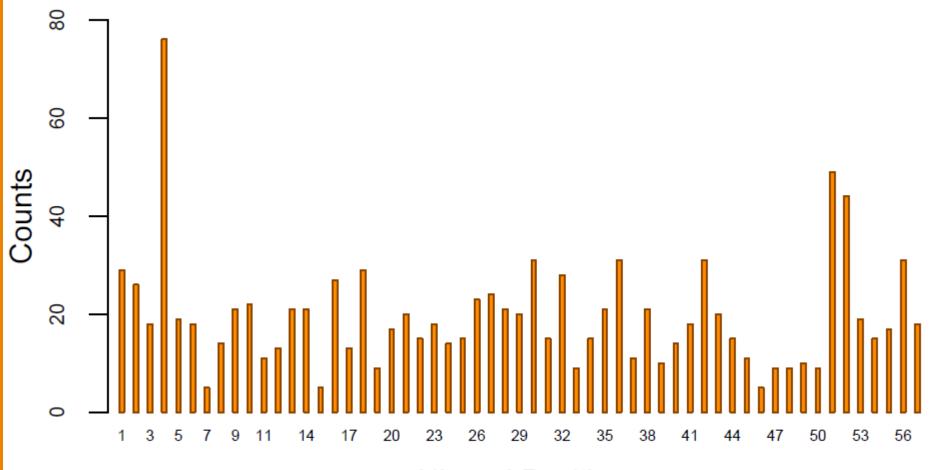
LineUp Approach

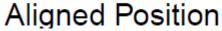


- Align sequences from all matching domains across all tumor types
- Evaluate missense mutation frequencies
- Applies to ~40% of missense mutations



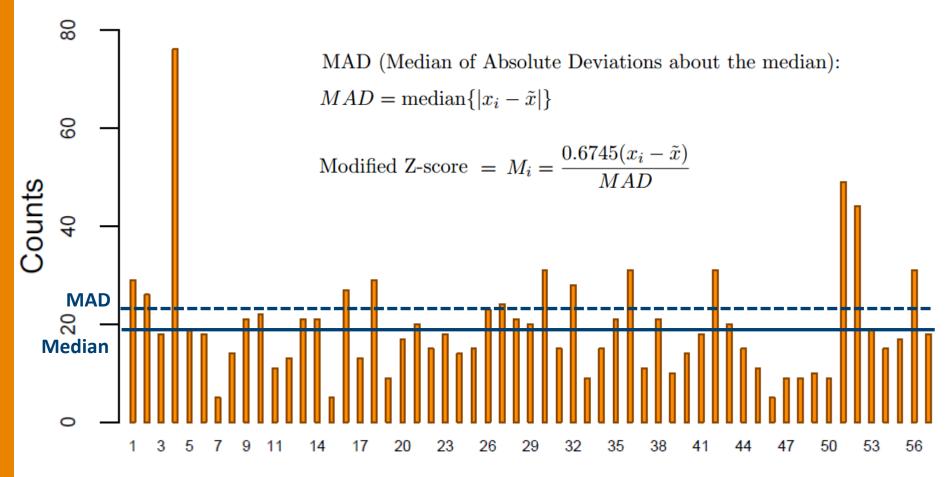
Mutations per position for two hundred aligned Homeobox domains across twenty tumor types







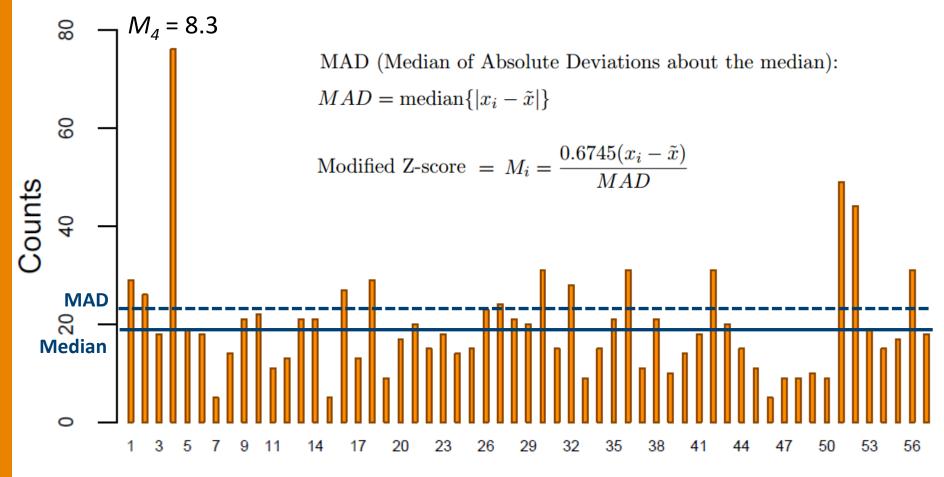
Identifying outliers: Modified Z-score



Aligned Position



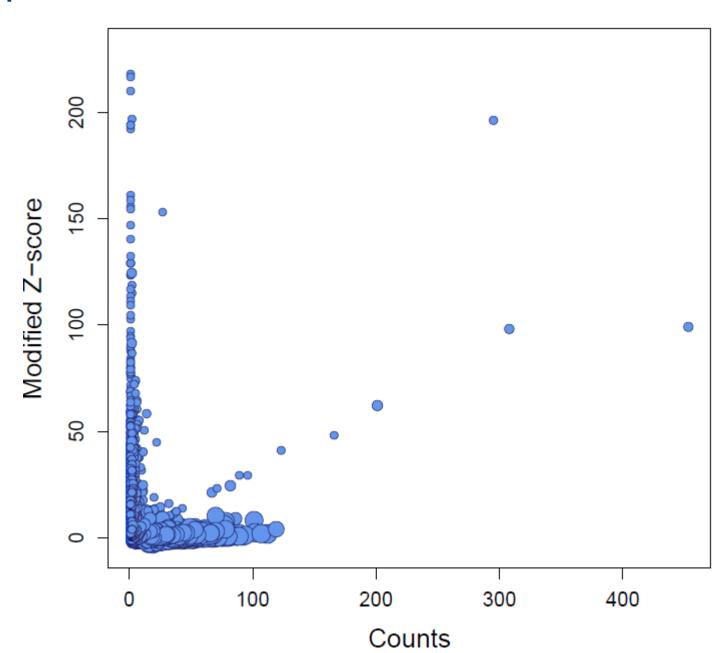
Identifying outliers: Modified Z-score



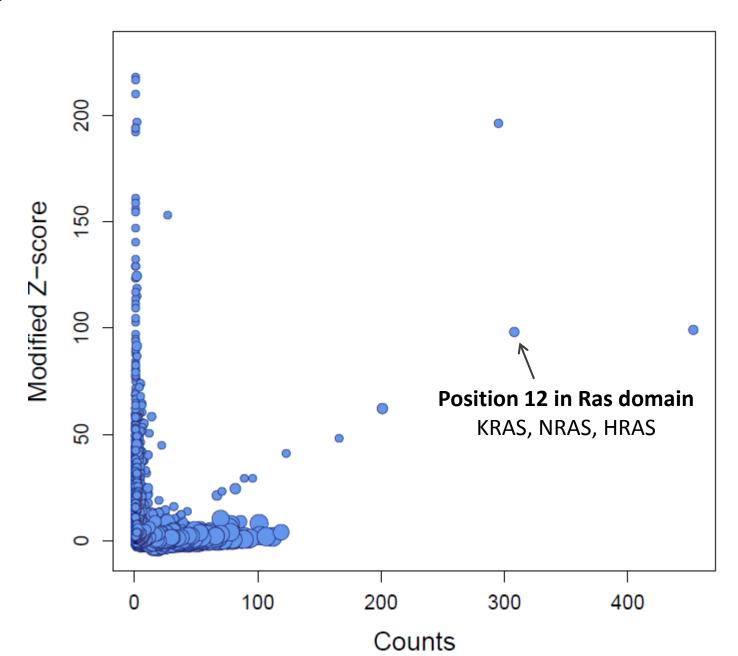
Aligned Position



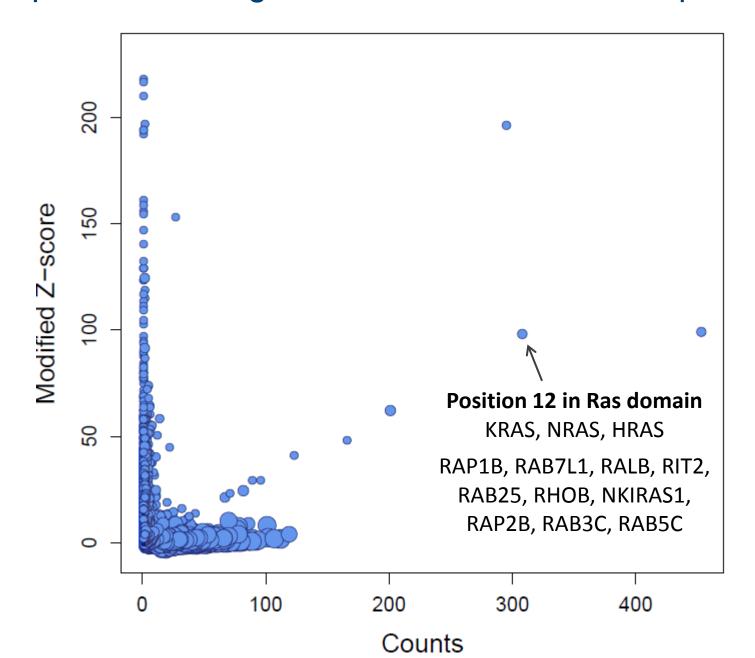
All positions within all domains



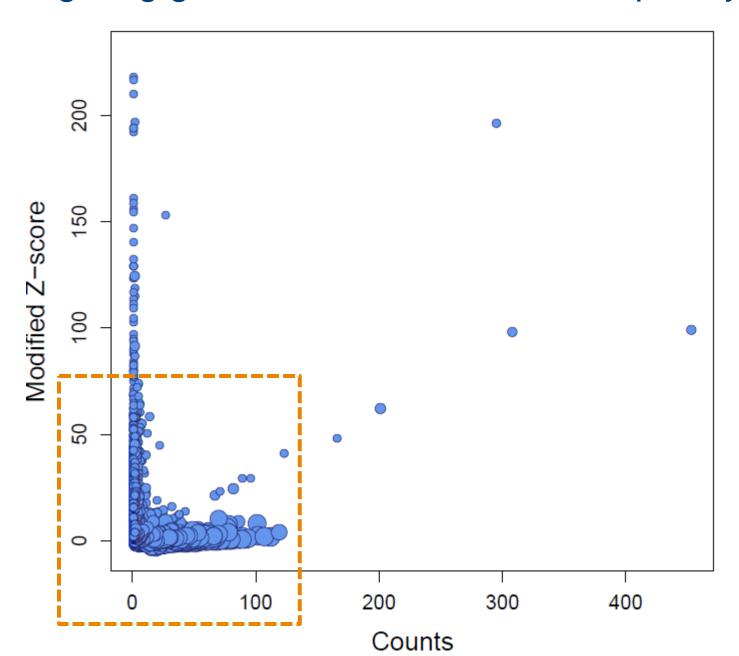
High Modified Z-score and counts for Ras domain



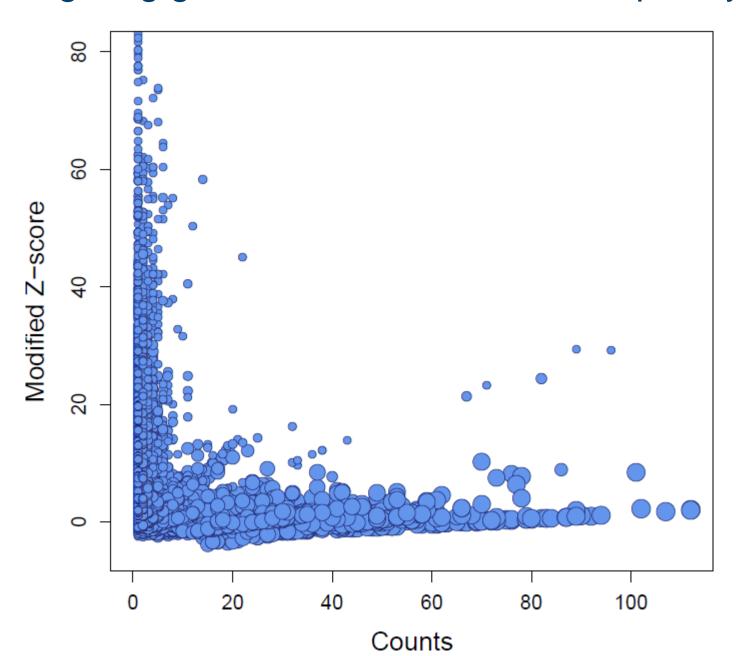
Multiple other Ras genes mutated at the same position



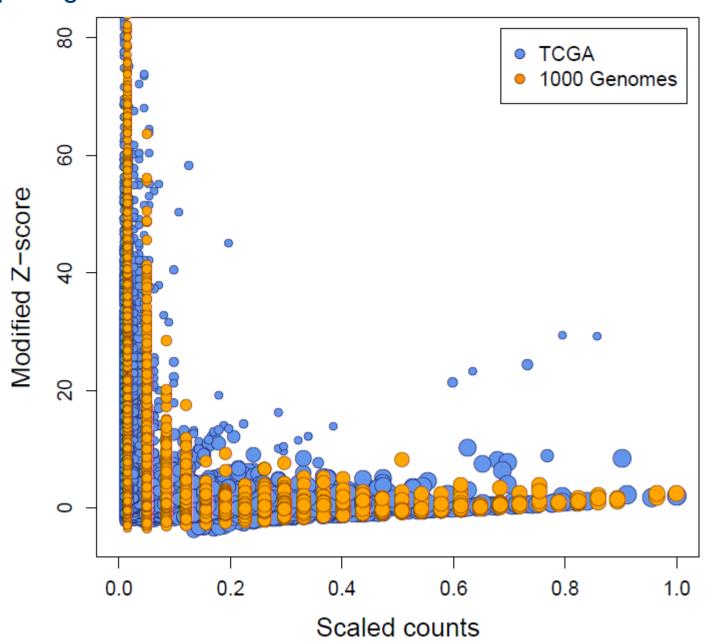
Investigating genes with low mutation frequency



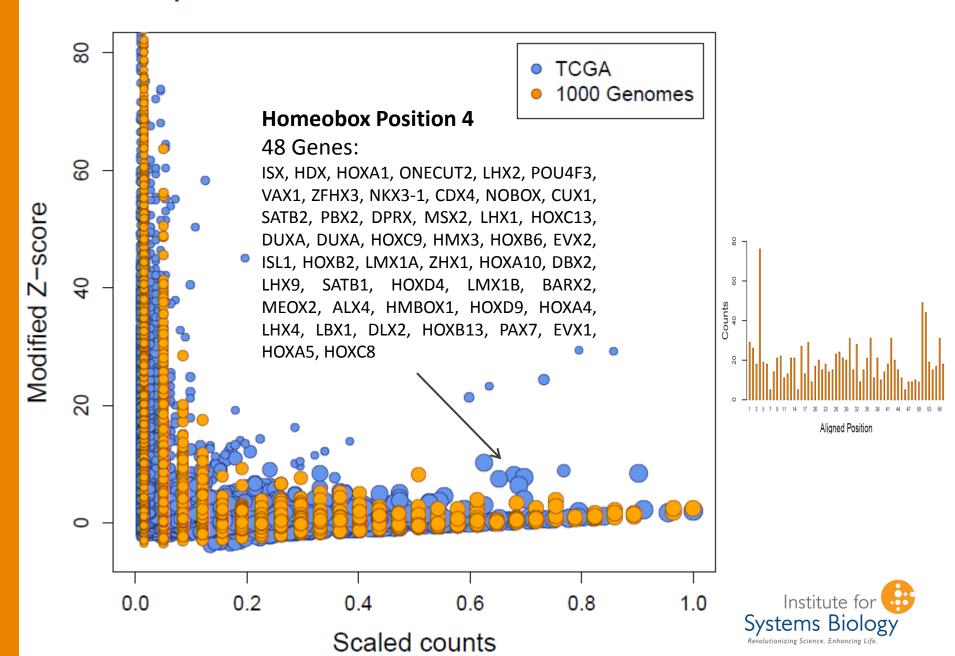
Investigating genes with low mutation frequency



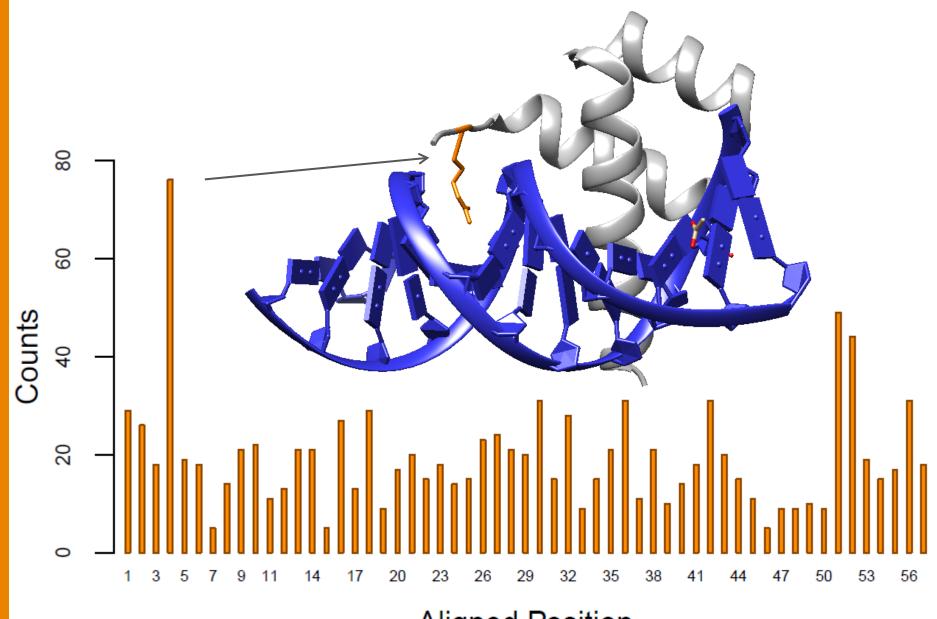
Background expectation: Comparing TCGA to 1000 Genomes



Outlier position within Homeobox domain



Structural interpretation



Aligned Position

Summary and Next Steps

- We have comprehensively evaluated mutations at all positions within all domains to identify low frequency but likely deleterious mutations
- Hotspots outside of domains and mutations that broadly disrupt structure and function not addressed
 - Integration with other methods is essential
- Functional validation of low frequency events in such data sets remains challenging
- As cancer and normal genome data size increases, more robust normalization per position per domain can be achieved



Acknowledgements



Ilya Shmulevich

Tae Denwongkun

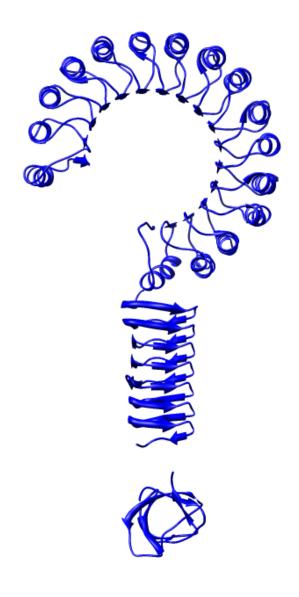
Theo Knijnenburg

Vesteinn Thorsson Kalle Leinonen Richard Kreisberg Hector Rovira Sheila Reynolds Lisa Iype Natalie Tasman











Example approaches and methods

Statistical assessment of multiple samples (MutSig, MuSiC, ...)

Mutational heterogeneity in cancer and the search for new cancer-associated games

Michael S. Lawrence^{1*}, Petar Stojanov^{1,2*}, Paz Pol: Scott L. Carter¹, Chip Stewart¹, Craig H. Mermel^{1,5}, 'Yotam Drier^{1,3,5,8}, Lihua Zou¹, Alex H. Ramos¹, Tre Carrie Sougnez¹, Lauren Ambrogio¹, Elizabeth Nicl Douglas Voet¹, Michael Noble¹, Daniel DiCara¹, Pei

MuSiC: Identifying mutational significance in cancer genomes

Nathan D. Dees, ^{1,4} Qunyuan Zhang, ^{1,4} Cyriac Kandoth, ¹ Michael C. Wendl, ^{1,2} William Schierding, ¹ Daniel C. Koboldt, ¹ Thomas B. Mooney, ¹ Matthew B. Callaway, ¹ David Dooling, ¹ Elaine R. Mardis, ^{1,2,3} Richard K. Wilson, ^{1,2,3} and Li Ding ^{1,2,5}

Sequence conservation (MutationAssessor, SIFT, ...)

Predicting the functional impact of protein mutations: appliant to account accounts.

Boris Reva*, Yevgeniy An

Predicting Deleterious Amino Acid Substitutions

Pauline C. Ng1,2 and Steven Henikoff1,3,4

Machine learning and classification (PolyPhen-2, CHASM, ...)

A method and server for predicting damaging missense mutations

Ivan A. Adzhubei^{1,7} Gerasimova⁵, Peer Cancer-Specific High-Throughput Annotation of Somatic Mutations: Computational Prediction of Driver Missense Mutations

Hannah Carter, Sining Chen, Leyla Isik, Svitlana Tyekucheva, Victor E. Velculescu, Kenneth W. Kinzler, Bert Vogelstein, and Rachel Karchin