



**KOÇ  
ÜNİVERSİTESİ**

# Yaşam bilimleri için yapay öğrenme

**Mehmet Gönen**  
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Hesaplamalı Biyoloji Bölümü, Tıp Fakültesi

2 Temmuz 2018



# Giriş

## Yaşam bilimleri uygulamalarındaki zorluklar

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- Çok az eğitim örneği ile karmaşık problemlerin çözülmesi



# Giriş

## Yaşam bilimleri uygulamalarındaki zorluklar

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- Çok az eğitim örneği ile karmaşık problemlerin çözülmesi
- Çeşitli veri kaynaklarının beraberce modellenmesi



# Giriş

## Yaşam bilimleri uygulamalarındaki zorluklar

---

- Çok az eğitim örneği ile karmaşık problemlerin çözülmesi
- Çeşitli veri kaynaklarının beraberce modellenmesi
- Test edilebilir hipotezler üretilmesi



# Giriş

## Yaşam bilimleri uygulamalarındaki zorluklar

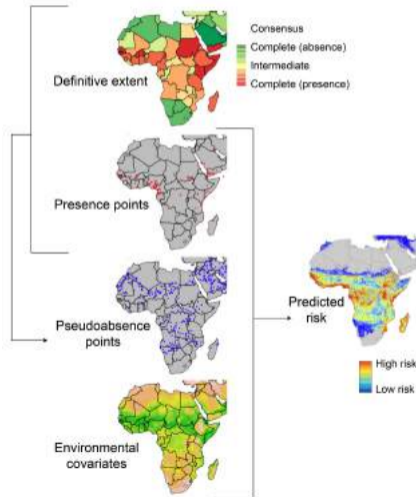
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- Çok az eğitim örneği ile karmaşık problemlerin çözülmesi
- Çeşitli veri kaynaklarının beraberce modellenmesi
- Test edilebilir hipotezler üretilmesi
- **Çekirdek tabanlı yapay öğrenme yöntemleri**

# **Enfeksiyon hastalıklarının modellenmesi**



# Enfeksiyon hastalıklarının modellenmesi

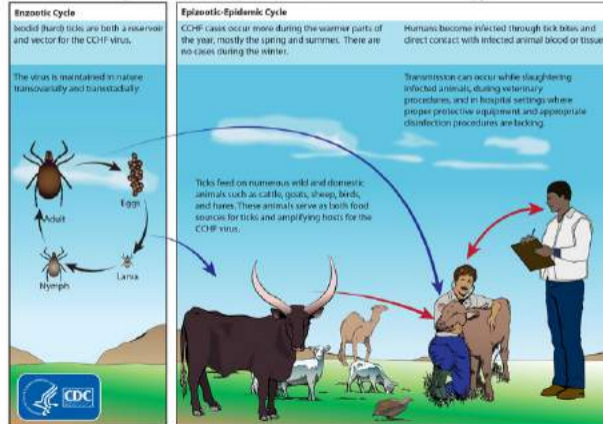




# Enfeksiyon hastalıklarının modellenmesi

## Kırım-Kongo Kanamalı Ateşi (KKKA) hastalığı

### Crimean-Congo Hemorrhagic Fever (CCHF) Virus Ecology

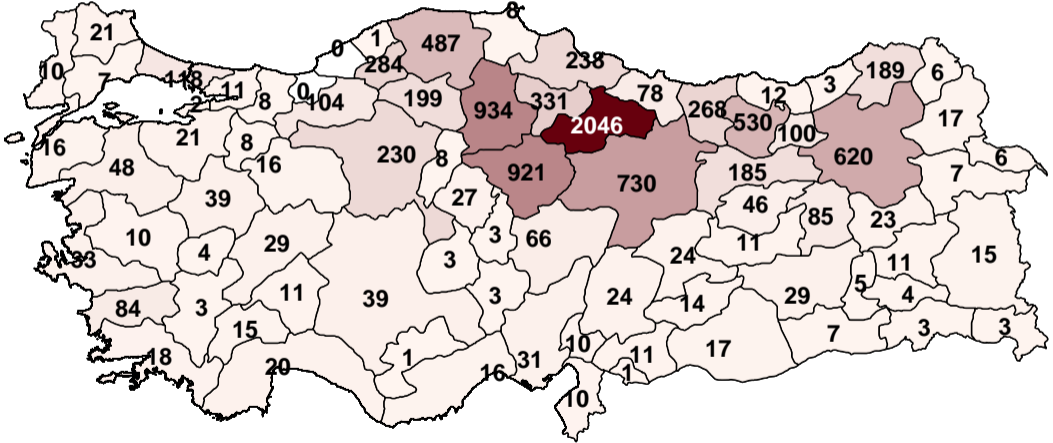






# Enfeksiyon hastalıklarının modellenmesi

## Türkiye'de KKKA





# Enfeksiyon hastalıklarının modellenmesi

## Türkiye'de KKKA

												Season	
Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total	Year
0	0	2	9	24	62	101	44	6	1	0	0	249	2004
0	0	0	8	27	77	95	51	3	4	0	0	265	2005
0	0	1	19	65	160	114	72	8	0	0	0	439	2006
0	0	2	25	119	216	224	90	40	1	0	0	717	2007
0	0	1	37	241	432	411	151	40	2	0	0	1315	2008
0	0	0	37	205	496	366	177	33	3	1	0	1318	2009
0	0	0	61	240	272	222	59	11	2	0	0	867	2010
0	0	1	29	149	341	349	180	19	5	2	0	1075	2011
0	0	1	31	223	233	201	90	13	3	1	0	796	2012
0	0	1	74	225	260	254	81	11	2	2	0	910	2013
0	4	6	95	218	238	280	108	13	5	0	0	967	2014
0	0	2	16	97	231	218	119	20	12	2	1	718	2015
0	4	17	441	1833	3018	2835	1222	217	40	8	1	9636	Total



# Enfeksiyon hastalıklarının modellenmesi

## Gauss süreci regresyon modeli

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$$\mathbf{y} = \mathbf{f} + \boldsymbol{\xi}$$

$$\mathbf{f} | \mathbf{X} \sim \text{Normal}(\mathbf{f}; \mathbf{0}, \mathbf{K})$$

$$\boldsymbol{\xi} | \sigma_y^2 \sim \text{Normal}(\boldsymbol{\xi}; \mathbf{0}, \sigma_y^2 \mathbf{I})$$



# Enfeksiyon hastalıklarının modellenmesi

## Gauss süreci regresyon modeli

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$$\boldsymbol{\xi} | \sigma_y^2 \sim \text{Normal}(\boldsymbol{\xi}; \mathbf{0}, \sigma_y^2 \mathbf{I})$$

$$\mathbf{K} = \begin{bmatrix} k(\mathbf{x}_1, \mathbf{x}_1) & k(\mathbf{x}_2, \mathbf{x}_1) & \cdots & k(\mathbf{x}_N, \mathbf{x}_1) \\ k(\mathbf{x}_1, \mathbf{x}_2) & k(\mathbf{x}_2, \mathbf{x}_2) & \cdots & k(\mathbf{x}_N, \mathbf{x}_2) \\ \vdots & \vdots & \ddots & \vdots \\ k(\mathbf{x}_1, \mathbf{x}_N) & k(\mathbf{x}_2, \mathbf{x}_N) & \cdots & k(\mathbf{x}_N, \mathbf{x}_N) \end{bmatrix}$$



# Enfeksiyon hastalıklarının modellenmesi

## Gauss süreci regresyon modeli

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$$\mathbb{E}[y_* | \mathbf{x}_*, \mathbf{X}, \mathbf{y}, \sigma_y^2] = \mathbf{k}_*^\top (\mathbf{K} + \sigma_y^2 \mathbf{I})^{-1} \mathbf{y}$$

$$\text{Var}[y_* | \mathbf{x}_*, \mathbf{X}, \mathbf{y}, \sigma_y^2] = k(x_*, x_*) - \mathbf{k}_*^\top (\mathbf{K} + \sigma_y^2 \mathbf{I})^{-1} \mathbf{k}_*$$



# Enfeksiyon hastalıklarının modellenmesi

## Yapısal Gauss süreci regresyon modeli

---

$$k(\mathbf{x}_i, \mathbf{x}_j) = k((\mathbf{s}_l, \mathbf{t}_p), (\mathbf{s}_m, \mathbf{t}_q)) = k_s(\mathbf{s}_l, \mathbf{s}_m)k_t(\mathbf{t}_p, \mathbf{t}_q)$$



# Enfeksiyon hastalıklarının modellenmesi

## Yapısal Gauss süreci regresyon modeli

---

$$k(\mathbf{x}_i, \mathbf{x}_j) = k((\mathbf{s}_l, \mathbf{t}_p), (\mathbf{s}_m, \mathbf{t}_q)) = k_s(\mathbf{s}_l, \mathbf{s}_m)k_t(\mathbf{t}_p, \mathbf{t}_q)$$

$$\mathbf{K} = \mathbf{K}_s \otimes \mathbf{K}_t$$



# Enfeksiyon hastalıklarının modellenmesi

## Yapısal Gauss süreci regresyon modeli

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$$\mathbf{K} = \mathbf{K}_s \otimes \mathbf{K}_t$$

$$E[y_\star | \mathbf{x}_\star, \mathbf{X}, \mathbf{Y}, \sigma_y^2] = (\mathbf{k}_{s,\star} \otimes \mathbf{k}_{t,\star})^\top (\mathbf{K}_s \otimes \mathbf{K}_t + \sigma_y^2 \mathbf{I})^{-1} \text{vec}(\mathbf{Y})$$

$$\text{Var}[y_\star | \mathbf{x}_\star, \mathbf{X}, \mathbf{Y}, \sigma_y^2] = k_s(s_\star, s_\star)k_t(t_\star, t_\star) - (\mathbf{k}_{s,\star} \otimes \mathbf{k}_{t,\star})^\top (\mathbf{K}_s \otimes \mathbf{K}_t + \sigma_y^2 \mathbf{I})^{-1} (\mathbf{k}_{s,\star} \otimes \mathbf{k}_{t,\star})$$





# Enfeksiyon hastalıklarının modellenmesi

## Yapısal Gauss süreci regresyon modeli

---

$$\mathbf{K}_s = \mathbf{U}_s \mathbf{D}_s \mathbf{U}_s^\top$$

$$\mathbf{K}_t = \mathbf{U}_t \mathbf{D}_t \mathbf{U}_t^\top$$



# Enfeksiyon hastalıklarının modellenmesi

## Yapısal Gauss süreci regresyon modeli

---

$$\mathbf{K}_s = \mathbf{U}_s \mathbf{D}_s \mathbf{U}_s^\top$$

$$\mathbf{K}_t = \mathbf{U}_t \mathbf{D}_t \mathbf{U}_t^\top$$

$$\mathbf{K}_s \otimes \mathbf{K}_t = (\mathbf{U}_s \otimes \mathbf{U}_t)(\mathbf{D}_s \otimes \mathbf{D}_t)(\mathbf{U}_s \otimes \mathbf{U}_t)^\top$$



# Enfeksiyon hastalıklarının modellenmesi

## Yapısal Gauss süreci regresyon modeli

---

$$\mathbf{K}_s = \mathbf{U}_s \mathbf{D}_s \mathbf{U}_s^\top$$

$$\mathbf{K}_t = \mathbf{U}_t \mathbf{D}_t \mathbf{U}_t^\top$$

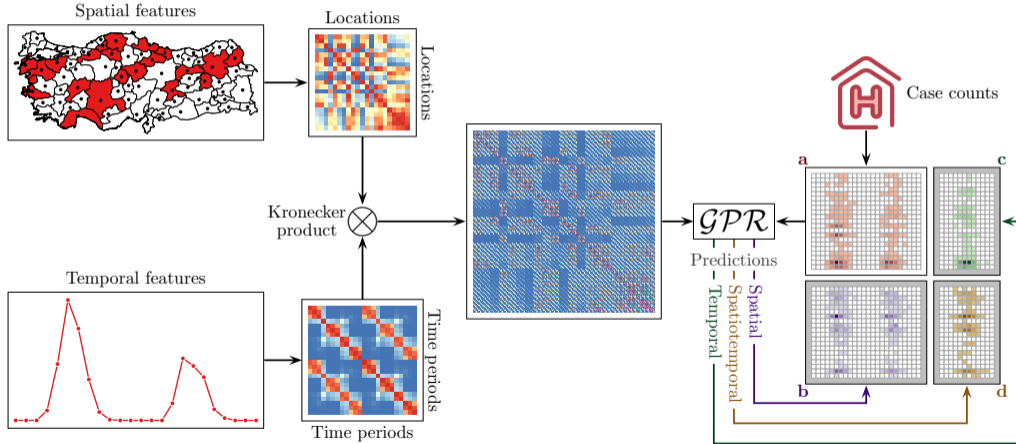
$$\mathbf{K}_s \otimes \mathbf{K}_t = (\mathbf{U}_s \otimes \mathbf{U}_t)(\mathbf{D}_s \otimes \mathbf{D}_t)(\mathbf{U}_s \otimes \mathbf{U}_t)^\top$$

$$(\mathbf{K}_s \otimes \mathbf{K}_t + \sigma_y^2 \mathbf{I})^{-1} = (\mathbf{U}_s \otimes \mathbf{U}_t)(\mathbf{D}_s \otimes \mathbf{D}_t + \sigma_y^2 \mathbf{I})^{-1}(\mathbf{U}_s \otimes \mathbf{U}_t)^\top$$



# Enfeksiyon hastalıklarının modellenmesi

Önerdiğimiz ilk model

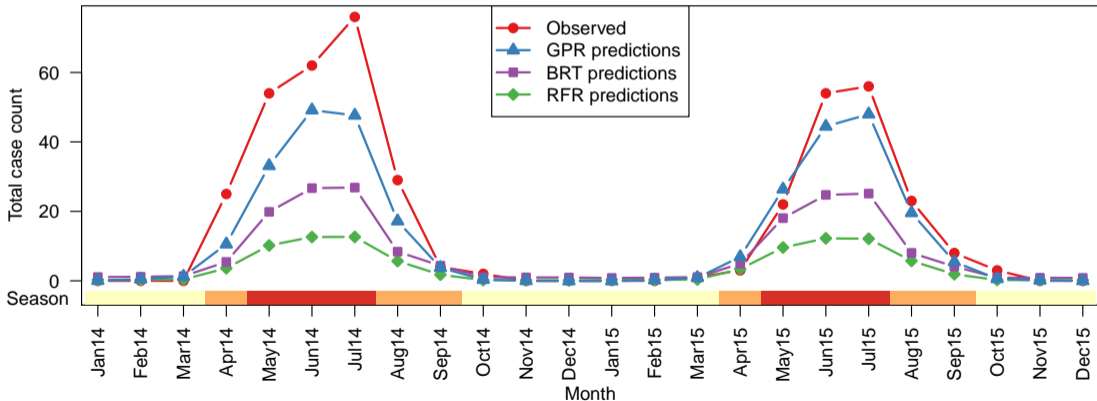




# Enfeksiyon hastalıklarının modellenmesi

## Kestirim sonuçları

### Spatial

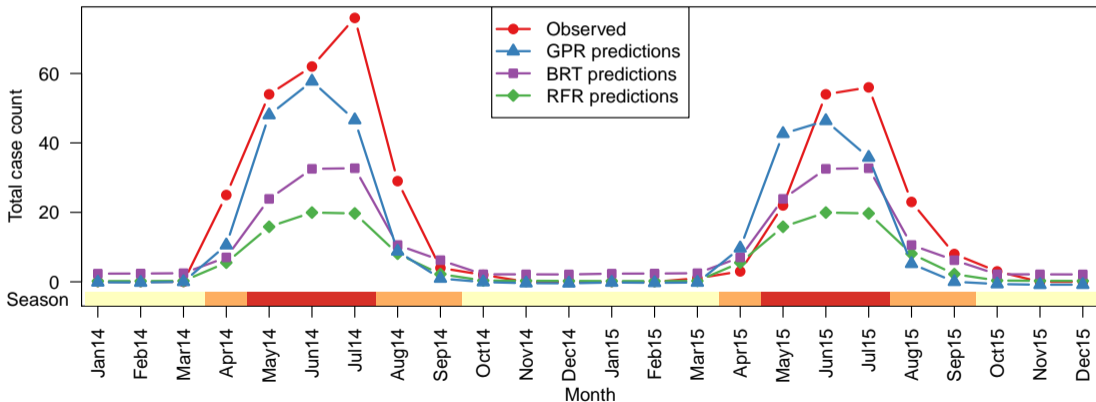




# Enfeksiyon hastalıklarının modellenmesi

## Kestirim sonuçları

### Temporal

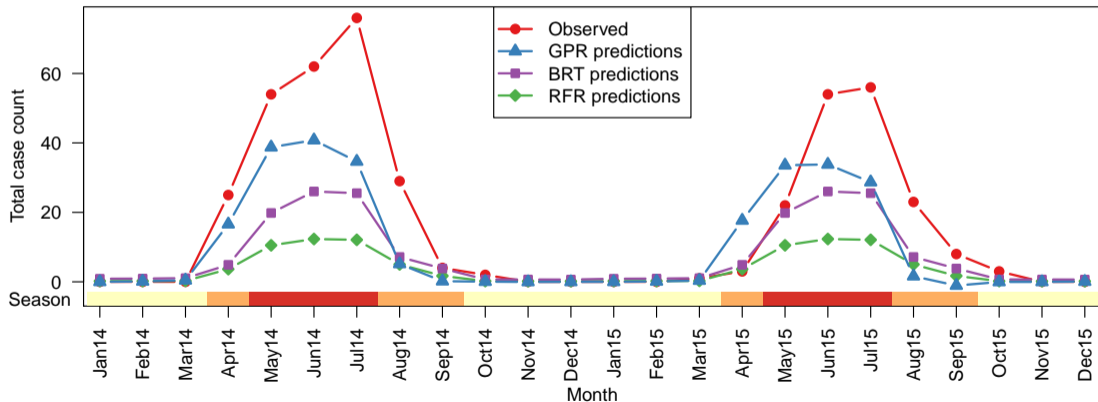




# Enfeksiyon hastalıklarının modellenmesi

## Kestirim sonuçları

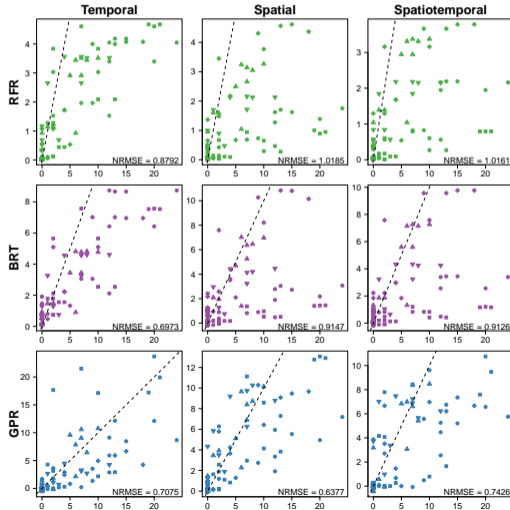
### Spatiotemporal





# Enfeksiyon hastalıklarının modellenmesi

## Kestirim sonuçları

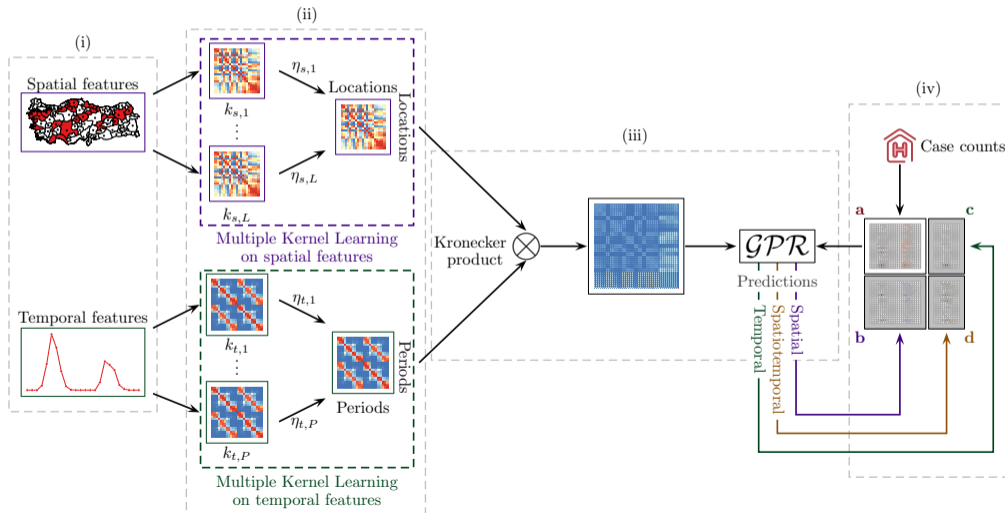






# Enfeksiyon hastalıklarının modellenmesi

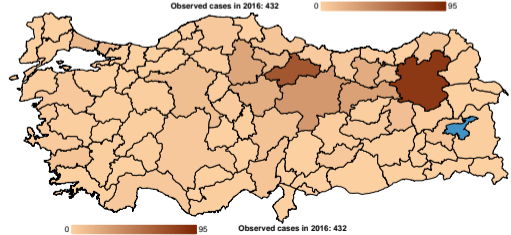
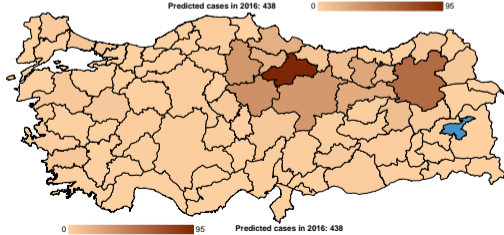
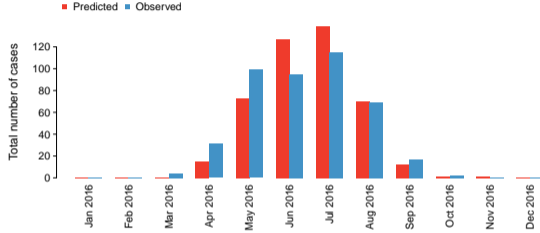
## Önerdiğimiz ikinci model





# Enfeksiyon hastalıklarının modellenmesi

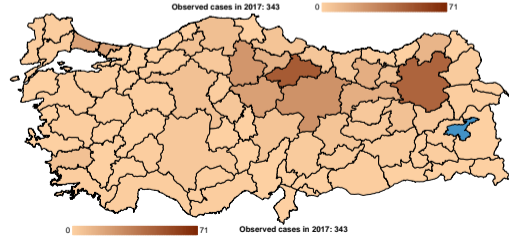
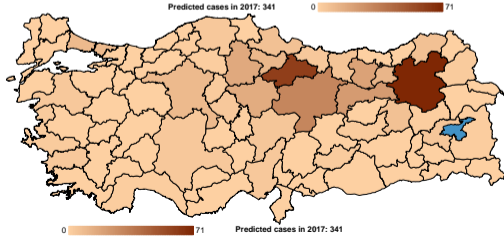
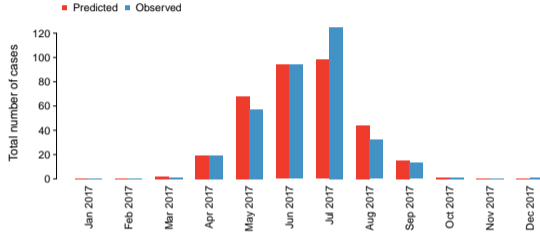
## 2016 yılı için kestirim sonuçları





# Enfeksiyon hastalıklarının modellenmesi

## 2017 yılı için kestirim sonuçları

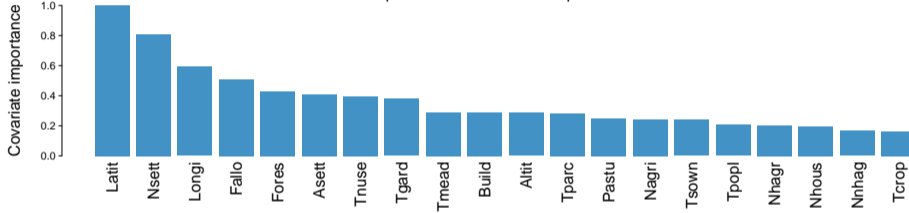




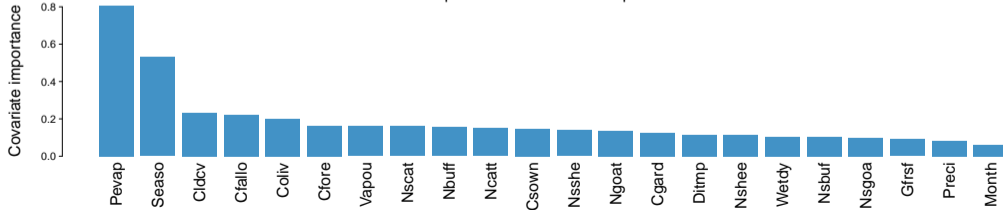
# Enfeksiyon hastalıklarının modellenmesi

## Öznitelik ağırlıkları

Spatial covariates for 2016 prediction



Temporal covariates for 2016 prediction

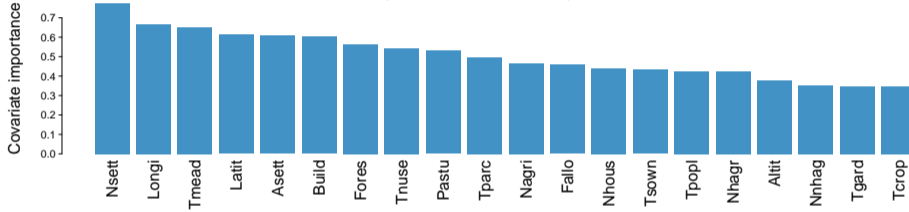




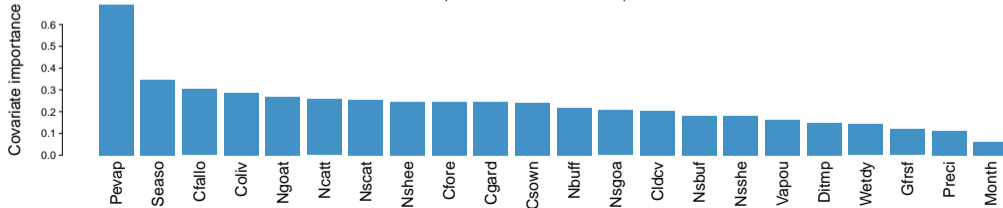
# Enfeksiyon hastalıklarının modellenmesi

## Öznitelik ağırlıkları

Spatial covariates for 2017 prediction



Temporal covariates for 2017 prediction

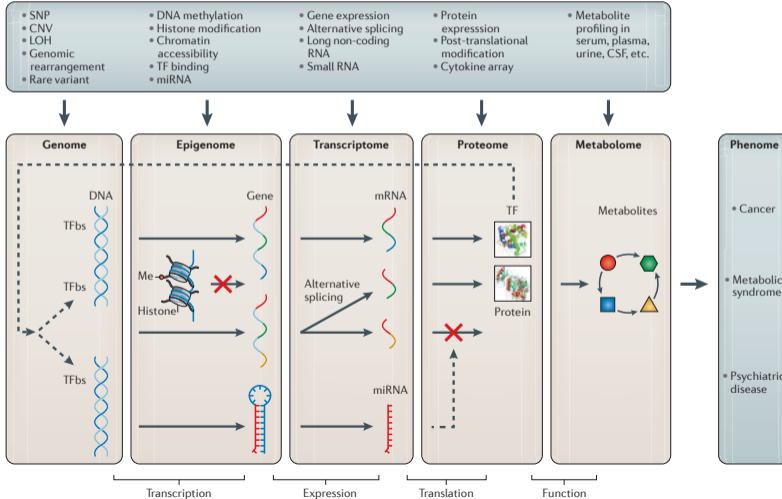


# **Karmaşık hastalıkların modellenmesi**



# Karmaşık hastalıkların modellenmesi

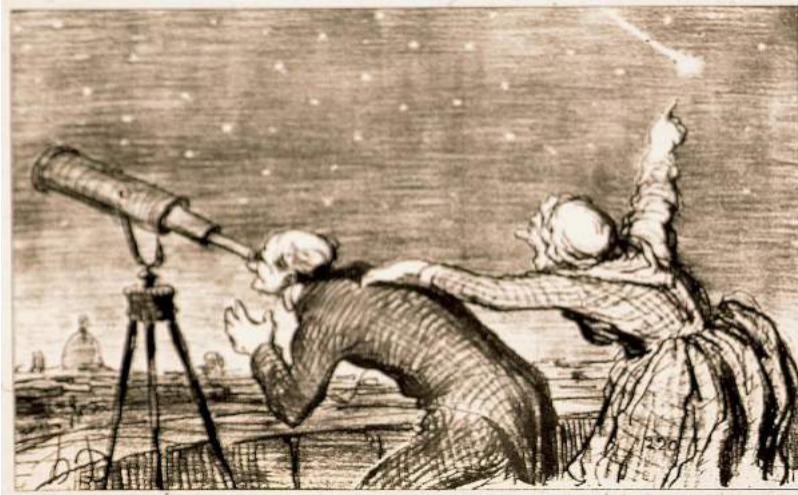
## Karmaşıklık nereden geliyor?





# Karmaşık hastalıkların modellenmesi

## Nereye bakmalıyız?

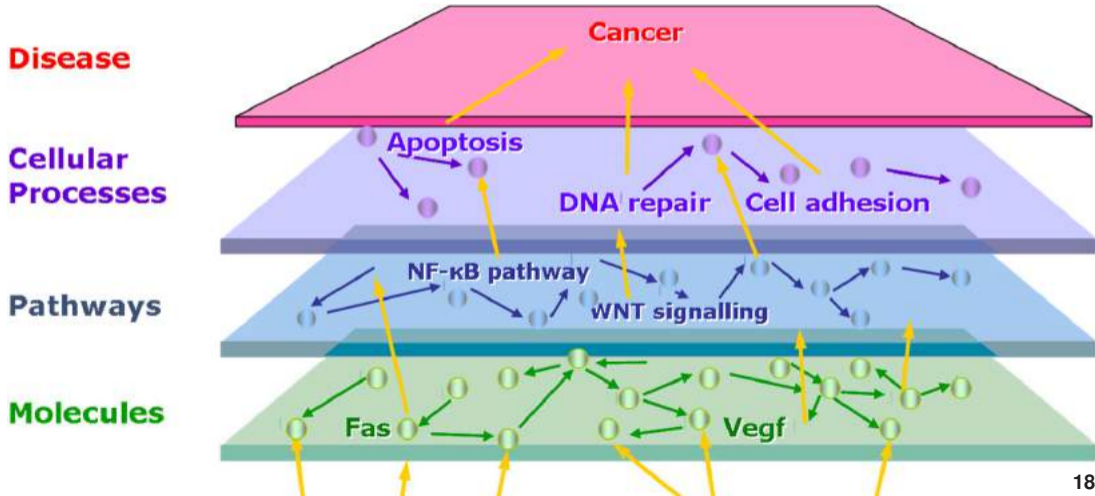






# Karmaşık hastalıkların modellenmesi

Neleri gözlemlemeliyiz?

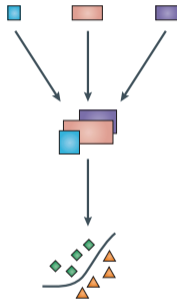




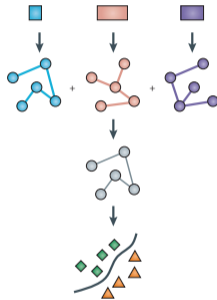
# Karmaşık hastalıkların modellenmesi

## Verileri nasıl birleştirmeliyiz?

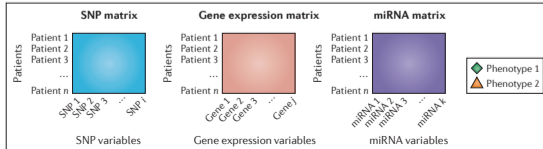
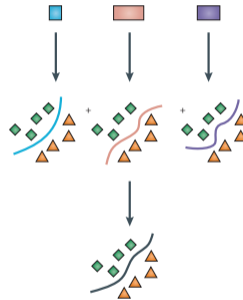
a Concatenation-based integration



b Transformation-based integration



c Model-based integration



# Pan-cancer transcriptional signatures predictive of oncogenic mutations reveal that Fbw7 regulates cancer cell oxidative metabolism

Ryan J. Davis<sup>a,b,c,1</sup>, Mehmet Gönen<sup>d,e,f,1</sup>, Daciana H. Margineantu<sup>a,b,1</sup>, Shlomo Handeli<sup>a,b</sup>, Jherek Swanger<sup>a,b</sup>, Pia Hoellerbauer<sup>a</sup>, Patrick J. Paddison<sup>a</sup>, Haiwei Gu<sup>g,h</sup>, Daniel Raftery<sup>g,h</sup>, Jonathan E. Grim<sup>b</sup>, David M. Hockenbery<sup>a,b,2</sup>, Adam A. Margolin<sup>d,2</sup>, and Bruce E. Clurman<sup>a,b,2,3</sup>

<sup>a</sup>Division of Human Biology, Fred Hutchinson Cancer Research Center, Seattle, WA 98109; <sup>b</sup>Division of Clinical Research, Fred Hutchinson Cancer Research Center, Seattle, WA 98109; <sup>c</sup>Molecular and Cellular Biology Graduate Program, University of Washington, Seattle, WA 98195; <sup>d</sup>Department of Biomedical Engineering, Oregon Health & Science University, Portland, OR 97239; <sup>e</sup>Department of Industrial Engineering, College of Engineering, Koç University, 34450 Istanbul, Turkey; <sup>f</sup>School of Medicine, Koç University, 34450 Istanbul, Turkey; <sup>g</sup>Northwest Metabolomics Research Center, University of Washington, Seattle, WA 98109; and <sup>h</sup>Division of Public Health Sciences, Fred Hutchinson Cancer Research Center, Seattle, WA 98109

c

## Kernelized Bayesian Transfer Learning\*

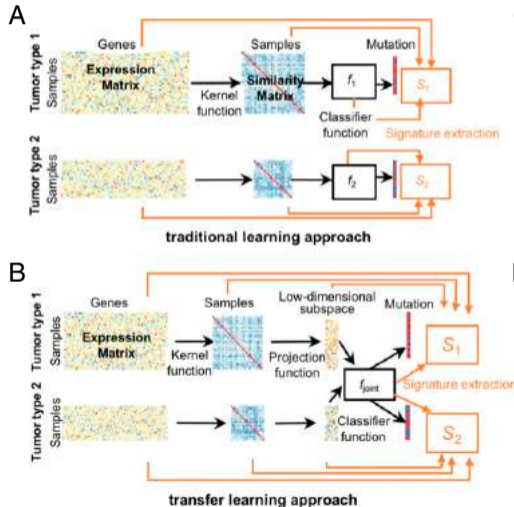
**Mehmet Gönen<sup>†</sup>**  
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**Adam A. Margolin<sup>†</sup>**  
adam.margolin@sagebase.org  
Sage Bionetworks  
Seattle, WA 98109, USA



# Karmaşık hastalıkların modellenmesi

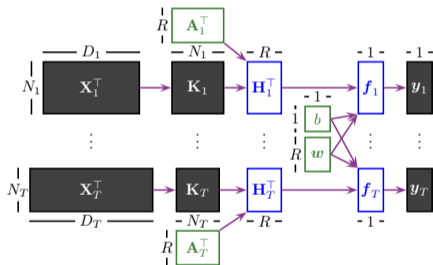
## Farklı hastalıkların transfer öğrenimi ile modellenmesi





# Karmaşık hastalıkların modellenmesi

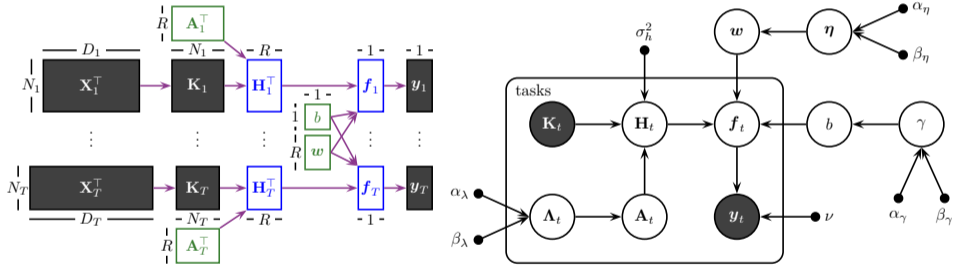
## Önerilen model





# Karmaşık hastalıkların modellenmesi

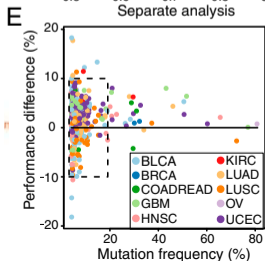
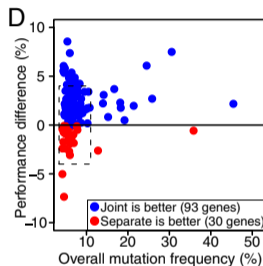
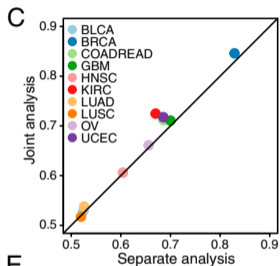
## Önerilen model





# Karmaşık hastalıkların modellenmesi

## Farklı hastalıkların transfer öğrenimi ile modellenmesi



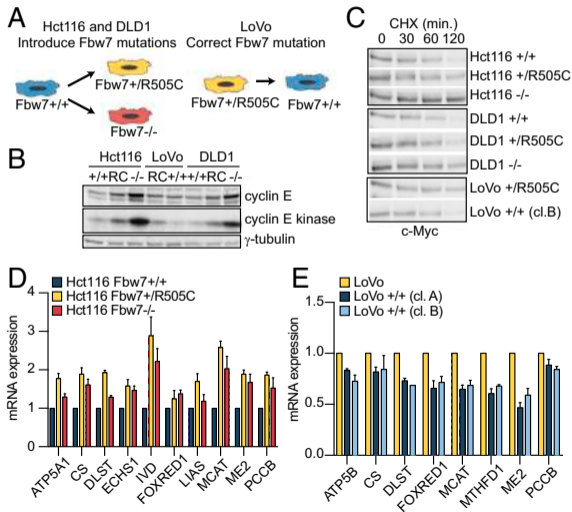
**F**

Tumor Type	Separate Analysis Rank	Joint Analysis Rank
<b>Consensus</b>	<b>56</b>	<b>1</b>
BLCA	54	3
COADREAD	7	1
HNSC	1	2
LUSC	NA	67
UCEC	2	1



# Karmaşık hastalıkların modellenmesi

## Farklı hastalıkların transfer öğrenimi ile modellenmesi

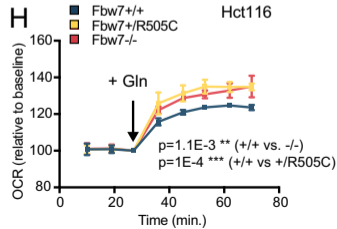
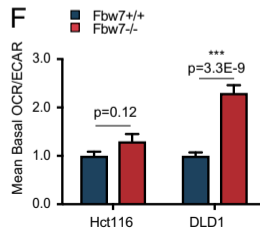
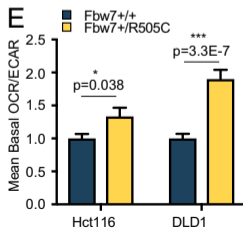
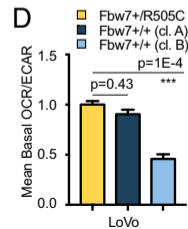
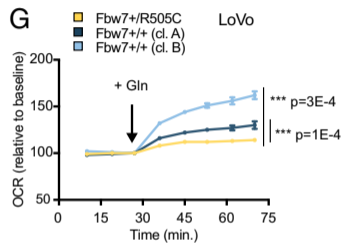
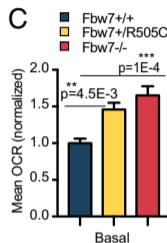
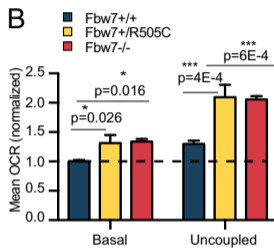
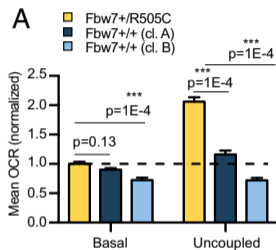






# Karmaşık hastalıkların modellenmesi

## Farklı hastalıkların transfer öğrenimi ile modellenmesi



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# Discriminating early- and late-stage cancers using multiple kernel learning on gene sets

Arezou Rahimi<sup>1</sup> and Mehmet Gönen<sup>2,3,4,\*</sup>

<sup>1</sup>Graduate School of Sciences and Engineering, <sup>2</sup>Department of Industrial Engineering, College of Engineering,

<sup>3</sup>School of Medicine, Koç University, İstanbul 34450, Turkey and <sup>4</sup>Department of Biomedical Engineering, School of Medicine, Oregon Health & Science University, Portland, OR 97239, USA

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# Karmaşık hastalıkların modellenmesi

## Erken ve geç aşama tümörlerinin ayrıştırılması

Cohort	Disease name	Stage I	Stage II	Stage III	Stage IV	Early (E1)	Late (E1)	Total (E1)	Early (E2)	Late (E2)	Total (E2)
ACC	Adrenocortical carcinoma	9	37	16	15	—	—	—	46	31	77
BLCA	Bladder urothelial carcinoma	2	130	140	134	—	—	—	132	274	406
BRCA	Breast invasive carcinoma	181	619	247	20	181	886	1067	800	267	1067
COAD	Colon adenocarcinoma	75	176	128	64	75	368	443	251	192	443
ESCA	Esophageal carcinoma	16	69	49	8	16	126	142	85	57	142
HNSC	Head and neck squamous cell carcinoma	25	70	78	259	25	407	429	95	337	429
KICH	Kidney chromophobe	20	25	14	6	20	45	65	45	20	65
KIRC	Kidney renal clear cell carcinoma	265	57	123	82	265	262	527	322	205	527
KIRP	Kidney renal papillary cell carcinoma	172	21	51	15	172	87	259	193	66	259
LIHC	Liver hepatocellular carcinoma	171	86	85	5	171	176	347	257	90	347
LUAD	Lung adenocarcinoma	274	121	84	26	274	231	505	395	110	505
LUSC	Lung squamous cell carcinoma	244	162	84	7	244	253	497	406	91	497
MESO	Mesothelioma	10	16	44	16	—	—	—	26	60	86
PAAD	Pancreatic adenocarcinoma	21	146	3	4	21	153	174	—	—	—
READ	Rectum adenocarcinoma	30	51	51	24	30	126	156	81	75	156
SKCM	Skin cutaneous melanoma	2	66	27	3	—	—	—	68	30	98
STAD	Stomach adenocarcinoma	53	111	150	38	53	299	352	164	188	352
TGCT	Testicular germ cell tumours	55	12	14	0	55	26	81	—	—	—
THCA	Thyroid carcinoma	281	52	112	55	281	219	500	333	167	500
UVM	Uveal melanoma	0	39	36	4	—	—	—	39	40	79
					Total	1883	3664	5547	3738	2300	6038



# Karmaşık hastalıkların modellenmesi

Destek vektör makineleri

---

$$\min. \frac{1}{2} \mathbf{w}^\top \mathbf{w} + C \sum_{i=1}^N \xi_i$$

$$\text{w.r.t. } \mathbf{w} \in \mathbb{R}^D, \quad \boldsymbol{\xi} \in \mathbb{R}^N, \quad b \in \mathbb{R}$$

$$\text{s.t. } y_i(\mathbf{w}^\top \mathbf{x}_i + b) \geq 1 - \xi_i \quad \forall i$$

$$\xi_i \geq 0 \quad \forall i$$



# Karmaşık hastalıkların modellenmesi

## Destek vektör makineleri

---

$$\text{min.} \quad - \sum_{i=1}^N \alpha_i + \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j y_i y_j \mathbf{x}_i^\top \mathbf{x}_j$$

$$\text{w.r.t.} \quad \boldsymbol{\alpha} \in \mathbb{R}^N$$

$$\text{s.t.} \quad \sum_{i=1}^N \alpha_i y_i = 0$$

$$C \geq \alpha_i \geq 0 \quad \forall i$$



# Karmaşık hastalıkların modellenmesi

## Çok çekirdekli destek vektör makineleri

---

$$\min. \quad - \sum_{i=1}^N \alpha_i + \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j y_i y_j \sum_{m=1}^P \eta_m k_m(\mathbf{x}_i, \mathbf{x}_j)$$

$$\text{w.r.t. } \boldsymbol{\alpha} \in \mathbb{R}^N, \boldsymbol{\eta} \in \mathbb{R}^P$$

$$\text{s.t. } \sum_{i=1}^N \alpha_i y_i = 0$$

$$C \geq \alpha_i \geq 0 \quad \forall i$$

$$\sum_{m=1}^P \eta_m = 1$$

$$\eta_m \geq 0 \quad \forall m$$



# Karmaşık hastalıkların modellenmesi

## Çok çekirdekli destek vektör makineleri

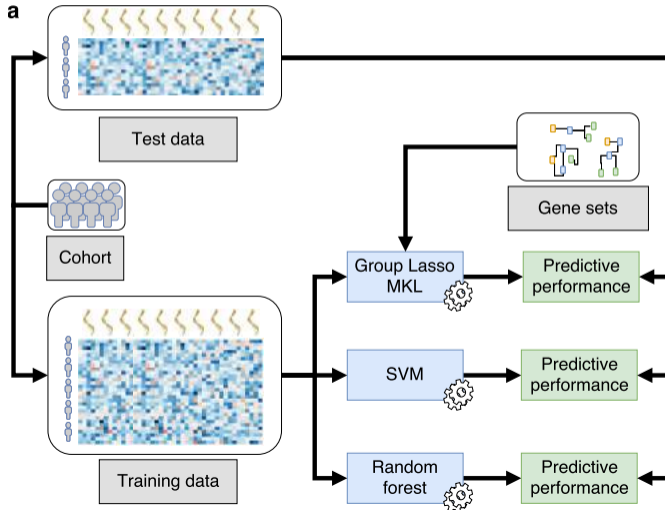
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$$\eta_m^{(t+1)} = \frac{\eta_m^{(t)} \sqrt{\sum_{i=1}^N \sum_{j=1}^N \alpha_i^{(t)} \alpha_j^{(t)} y_i y_j k_m(\mathbf{x}_i, \mathbf{x}_j)}}{\sum_{o=1}^P \eta_o^{(t)} \sqrt{\sum_{i=1}^N \sum_{j=1}^N \alpha_i^{(t)} \alpha_j^{(t)} y_i y_j k_o(\mathbf{x}_i, \mathbf{x}_j)}} \quad \forall m$$



# Karmaşık hastalıkların modellenmesi

## Önerdiğimiz yöntem



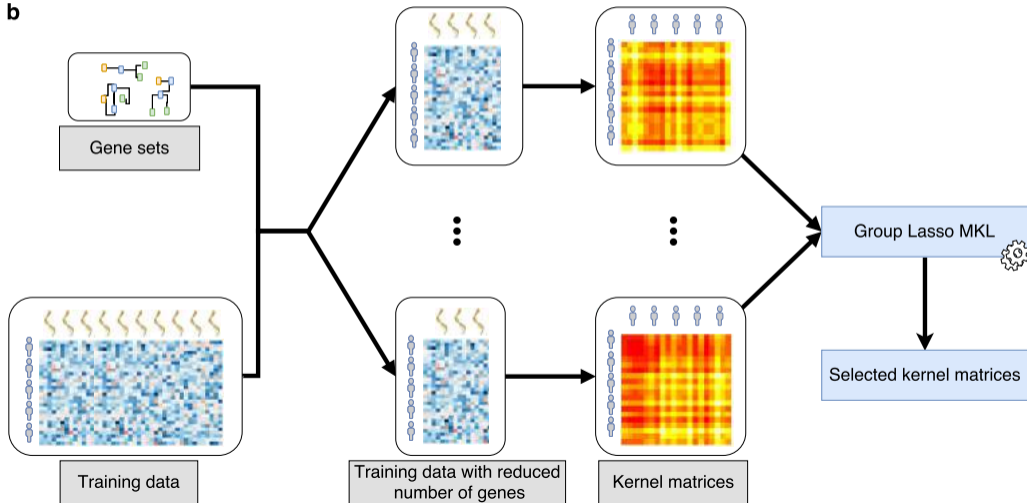




# Karmaşık hastalıkların modellenmesi

Önerdiğimiz yöntem

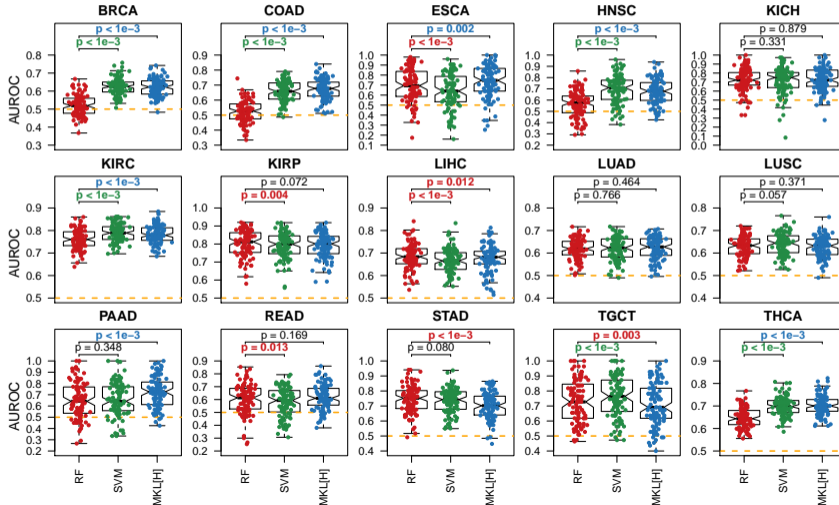
b





# Karmaşık hastalıkların modellenmesi

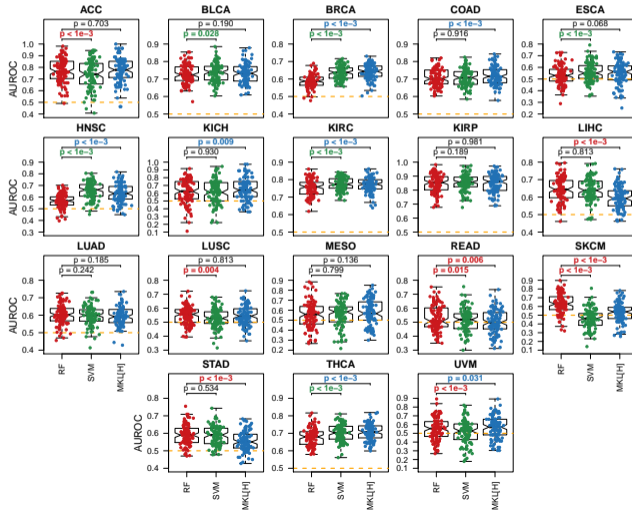
Kestirim sonuçları (Erken aşama: I. Geç aşama: II, III ve IV)

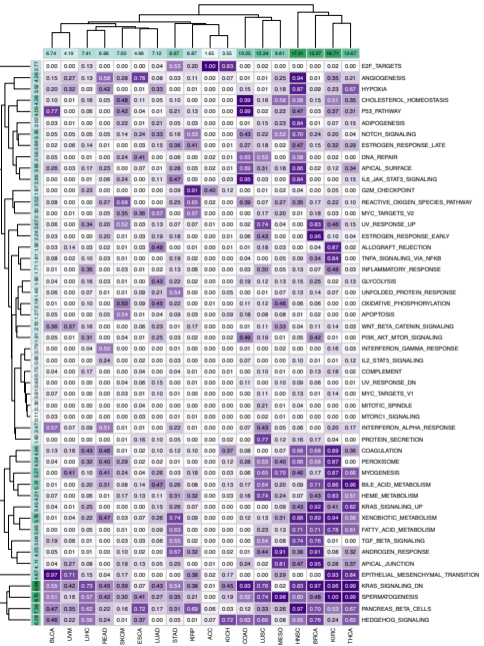
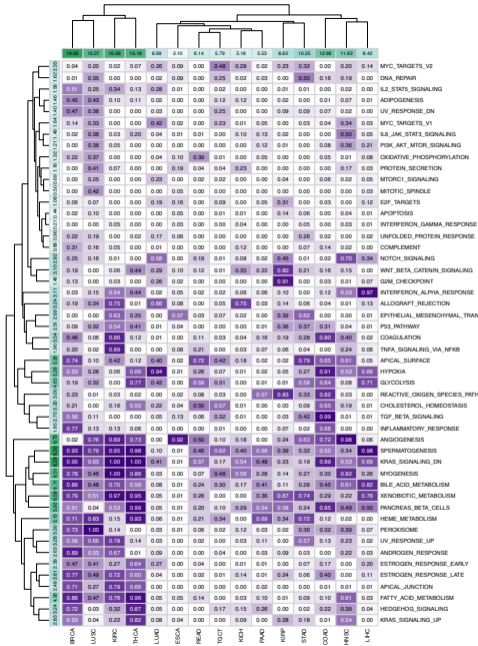




# Karmaşık hastalıkların modellenmesi

## Kestirim sonuçları (Erken aşama: I ve II. Geç aşama: III ve IV)

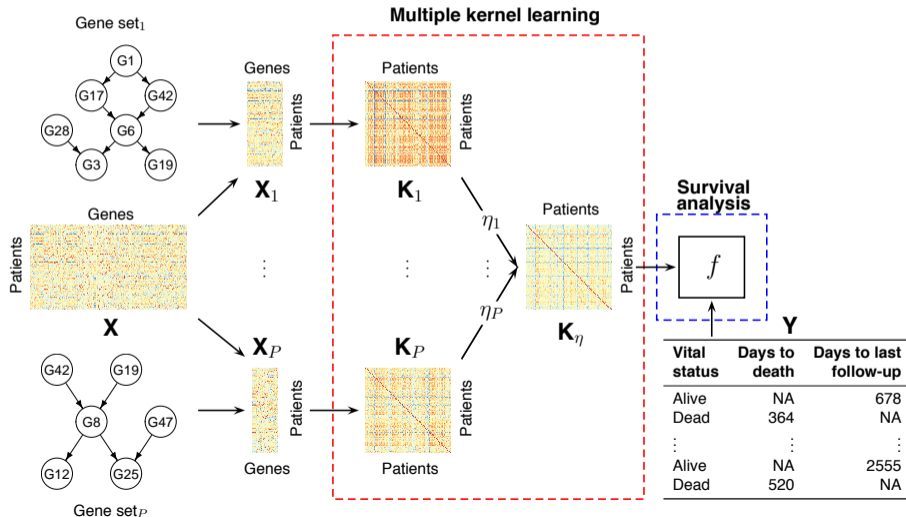






# Karmaşık hastalıkların modellenmesi

## Kanser hastalarının sağ kalım analizi





# Karmaşık hastalıkların modellenmesi

## Kanser hastalarının sağ kalım analizi



- 20 cancer types
- 7,655 patients



# Karmaşık hastalıkların modellenmesi

## Sağ kalım analizi için destek vektör makineleri

---

$$\min. \frac{1}{2} \mathbf{w}^\top \mathbf{w} + C \sum_{i=1}^N (\xi_i^+ + (1 - \delta_i) \xi_i^-)$$

$$\text{w.r.t. } \mathbf{w} \in \mathbb{R}^D, \quad \boldsymbol{\xi}^+ \in \mathbb{R}^N, \quad \boldsymbol{\xi}^- \in \mathbb{R}^N, \quad b \in \mathbb{R}$$

$$\text{s.t. } \epsilon + \xi_i^+ \geq y_i - \mathbf{w}^\top \mathbf{x}_i - b \quad \forall i$$

$$\epsilon + \xi_i^- \geq \mathbf{w}^\top \mathbf{x}_i + b - y_i \quad \forall i$$

$$\xi_i^+ \geq 0 \quad \forall i$$

$$\xi_i^- \geq 0 \quad \forall i$$



# Karmaşık hastalıkların modellenmesi

## Sağ kalım analizi için destek vektör makineleri

---

$$\text{min.} \quad - \sum_{i=1}^N y_i (\alpha_i^+ - \alpha_i^-) + \epsilon \sum_{i=1}^N (\alpha_i^+ + \alpha_i^-) + \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N (\alpha_i^+ - \alpha_i^-) (\alpha_j^+ - \alpha_j^-) \mathbf{x}_i^\top \mathbf{x}_j$$

$$\text{w.r.t.} \quad \boldsymbol{\alpha}^+ \in \mathbb{R}^N, \quad \boldsymbol{\alpha}^- \in \mathbb{R}^N$$

$$\text{s.t.} \quad \sum_{i=1}^N (\alpha_i^+ - \alpha_i^-) = 0$$

$$C \geq \alpha_i^+ \geq 0 \quad \forall i$$

$$C(1 - \delta_i) \geq \alpha_i^- \geq 0 \quad \forall i$$





# Karmaşık hastalıkların modellenmesi

Sağ kalım analizi için çok çekirdekli destek vektör makineleri

$$\min. - \sum_{i=1}^N y_i(\alpha_i^+ - \alpha_i^-) + \epsilon \sum_{i=1}^N (\alpha_i^+ + \alpha_i^-) + \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N (\alpha_i^+ - \alpha_i^-)(\alpha_j^+ - \alpha_j^-) \sum_{m=1}^P \eta_m k_m(\mathbf{x}_i, \mathbf{x}_j)$$

$$\text{w.r.t. } \boldsymbol{\alpha}^+ \in \mathbb{R}^N, \boldsymbol{\alpha}^- \in \mathbb{R}^N, \boldsymbol{\eta} \in \mathbb{R}^P$$

$$\text{s.t. } \sum_{i=1}^N (\alpha_i^+ - \alpha_i^-) = 0$$

$$C \geq \alpha_i^+ \geq 0 \quad \forall i$$

$$C(1 - \delta_i) \geq \alpha_i^- \geq 0 \quad \forall i$$

$$\sum_{m=1}^P \eta_m = 1$$

$$\eta_m \geq 0 \quad \forall m$$



# Karmaşık hastalıkların modellenmesi

## Sağ kalım analizi için çok çekirdekli destek vektör makineleri

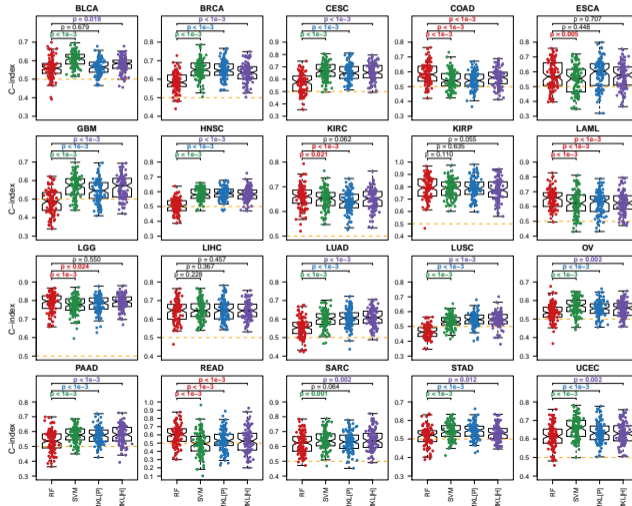
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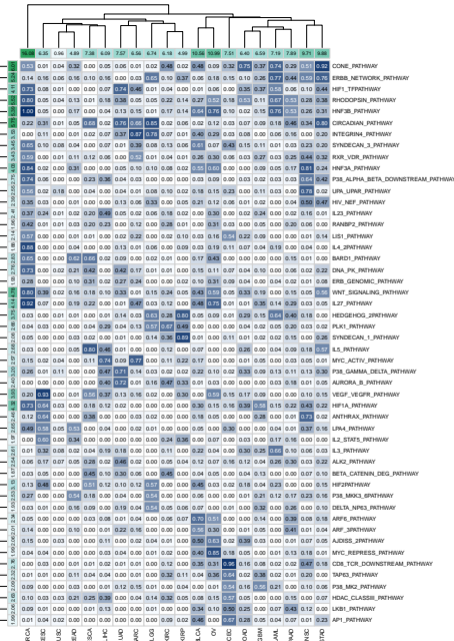
$$\eta_m^{(t+1)} = \frac{\eta_m^{(t)} \sqrt{\sum_{i=1}^N \sum_{j=1}^N (\alpha_i^{+(t)} - \alpha_i^{- (t)}) (\alpha_j^{+(t)} - \alpha_j^{- (t)}) k_m(\mathbf{x}_i, \mathbf{x}_j)}}{\sum_{o=1}^P \eta_o^{(t)} \sqrt{\sum_{i=1}^N \sum_{j=1}^N (\alpha_i^{+(t)} - \alpha_i^{- (t)}) (\alpha_j^{+(t)} - \alpha_j^{- (t)}) k_o(\mathbf{x}_i, \mathbf{x}_j)}} \quad \forall m$$



# Karmaşık hastalıkların modellenmesi

## Sağ kalım analizi kestirim sonuçları

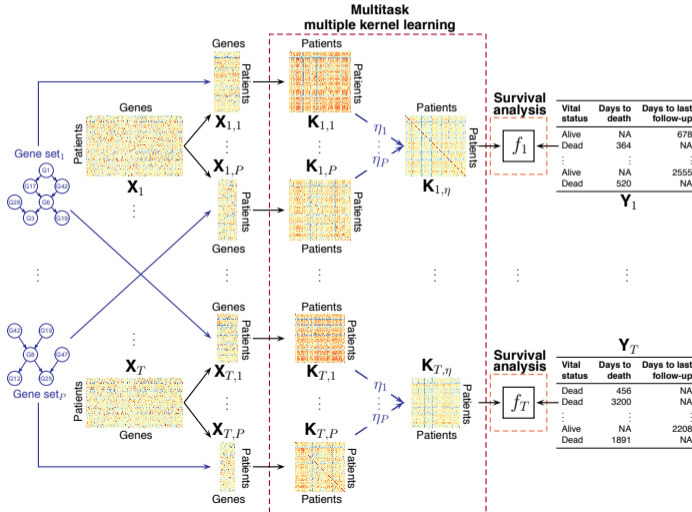


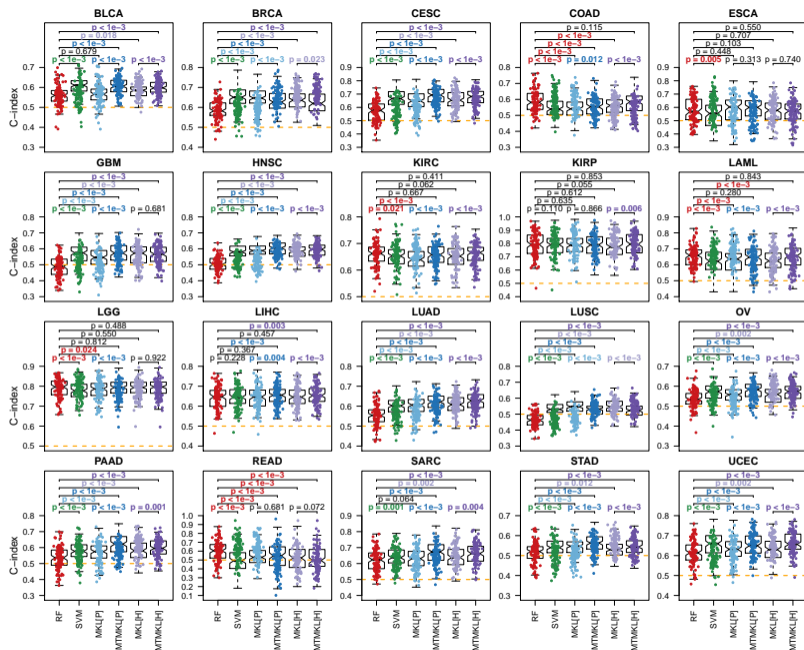


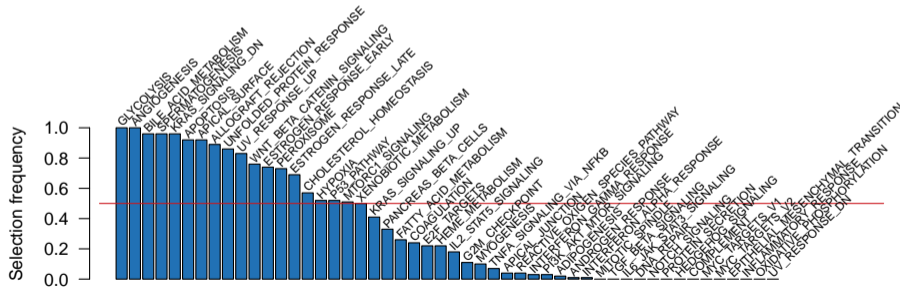
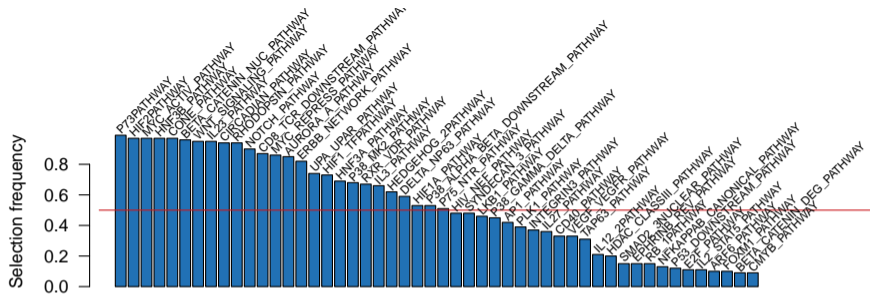


# Karmaşık hastalıkların modellenmesi

## Çoklu görev öğrenimi ile sağ kalım analizi









## Sonuç

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- Yaşam bilimleri uygulamaları için çekirdek tabanlı yapay öğrenme yöntemleri





## Sonuç

---

- Yaşam bilimleri uygulamaları için çekirdek tabanlı yapay öğrenme yöntemleri
- Az sayıda ve yüksek boyutlu örnekten öğrenebilme



## Sonuç

---

- Yaşam bilimleri uygulamaları için çekirdek tabanlı yapay öğrenme yöntemleri
- Az sayıda ve yüksek boyutlu örnekten öğrenebilme
- Farklı özellikteki veri kaynaklarını birleştirebilme



## Sonuç

---


- Yaşam bilimleri uygulamaları için çekirdek tabanlı yapay öğrenme yöntemleri
- Az sayıda ve yüksek boyutlu örnekten öğrenebilme
- Farklı özellikteki veri kaynaklarını birleştirebilme
- Test edilebilir hipotezler üretmeye uygun bilgi çıkarımı



# Sonuç

## Kaynak kodlar

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## Destekler

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- Türkiye Bilimsel ve Teknolojik Araştırma Kurumu (TÜBİTAK)
  - Hesaplamalı Onkoloji İçin Yolak Tabanlı Çekirdek Öğrenme Algoritmaları (EEEAG 117E181)
- Türkiye Bilimler Akademisi (TÜBA)
  - Üstün Başarılı Genç Bilim İnsanlarını Ödüllendirme Programı (GEBİP)
- Bilim Akademisi (BA)
  - Bilim Akademisi Genç Bilim İnsanları Ödül Programı (BAGEP)