# The embedding problem for Markov processes 

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## The embedding problem

## Definition

- A Markov matrix is a non-negative square matrix with row sum equal to one.
- A rate matrix is a real square matrix with row sum equal to zero and non-negative off-diagonal entries.

A Markov matrix $M$ is said to be embeddable if $M=\exp (Q)$ for some rate matrix $Q$. In this case, we say that $Q$ is a Markov generator for $M$.

## Embedding Problem (Elfving 1937)

Given a Markov matrix $M$, decide whether it is embeddable or not.

## The embedding problem

$2 \times 2 M$ embeddable $\Leftrightarrow \operatorname{det}(M)>0$ (Kingman 1962).
$3 \times 3$ Characterization split in cases depending on eigenvalues. (Cuthbert 1973, Johansen 1974, Chen 2011).
$n \times n$ Solved for some particular cases:

- Different and real eigenvalues (Singer 1976).
- Double-stochastic matrices (Jia 2016).
- Equal-input model (Baake-Sumner 2019).

In this talk:

- Different eigenvalues (real or not).
- $4 \times 4$ Markov matrices.


## Modelling evolution



## Modelling evolution





- Nucleotides are represented as the states of random variables.
- Nucleotide substitution is modelled as a Markov process.


## Markov Processes

Markov matrices encode the conditional substitution probabilities between states:

$$
M=\left(\begin{array}{llll}
P(\mathrm{~A} \rightarrow \mathrm{~A}) & P(\mathrm{~A} \rightarrow \mathrm{G}) & P(\mathrm{~A} \rightarrow \mathrm{C}) & P(\mathrm{~A} \rightarrow \mathrm{~T}) \\
P(\mathrm{G} \rightarrow \mathrm{~A}) & P(\mathrm{G} \rightarrow \mathrm{G}) & P(\mathrm{G} \rightarrow \mathrm{C}) & P(\mathrm{G} \rightarrow \mathrm{~T}) \\
P(\mathrm{C} \rightarrow \mathrm{~A}) & P(\mathrm{C} \rightarrow \mathrm{G}) & P(\mathrm{C} \rightarrow \mathrm{C}) & P(\mathrm{C} \rightarrow \mathrm{~T}) \\
P(\mathrm{~T} \rightarrow \mathrm{~A}) & P(\mathrm{~T} \rightarrow \mathrm{G}) & P(\mathrm{~T} \rightarrow \mathrm{C}) & P(\mathrm{~T} \rightarrow \mathrm{~T})
\end{array}\right)
$$

## Markov Processes

Markov matrices encode the conditional substitution probabilities between states:

$$
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P(\mathrm{~A} \rightarrow \mathrm{~A}) & P(\mathrm{~A} \rightarrow \mathrm{G}) & P(\mathrm{~A} \rightarrow \mathrm{C}) & P(\mathrm{~A} \rightarrow \mathrm{~T}) \\
P(\mathrm{G} \rightarrow \mathrm{~A}) & P(\mathrm{G} \rightarrow \mathrm{G}) & P(\mathrm{G} \rightarrow \mathrm{C}) & P(\mathrm{G} \rightarrow \mathrm{~T}) \\
P(\mathrm{C} \rightarrow \mathrm{~A}) & P(\mathrm{C} \rightarrow \mathrm{G}) & P(\mathrm{C} \rightarrow \mathrm{C}) & P(\mathrm{C} \rightarrow \mathrm{~T}) \\
P(\mathrm{~T} \rightarrow \mathrm{~A}) & P(\mathrm{~T} \rightarrow \mathrm{G}) & P(\mathrm{~T} \rightarrow \mathrm{C}) & P(\mathrm{~T} \rightarrow \mathrm{~T})
\end{array}\right)
$$

The change between probability distributions $\pi_{i}$ is computed as

$$
\begin{gathered}
\pi_{1}=\pi_{0} \cdot M \\
\pi_{X}^{1}=\pi_{\mathrm{A}}^{0} P(\mathrm{~A} \rightarrow x)+\pi_{\mathrm{G}}^{0} P(\mathrm{G} \rightarrow x)+\pi_{\mathrm{C}}^{0} P(\mathrm{c} \rightarrow x)+\pi_{\mathrm{T}}^{0} P(\mathrm{~T} \rightarrow x)
\end{gathered}
$$

## Markov Processes: Continuous Approach

## Hypothesis

- Substitution events ruled by the same instantaneous transition matrix $R$.
- Substitution events follow a homogeneous Poisson distribution.

Then the transition matrix corresponding to time $t$ is:
$M(t)=\sum_{k=0}^{\infty} \frac{(\mu t)^{k} \cdot e^{-\mu t}}{k!} R^{k}=\cdots=e^{Q t}, \quad$ where $Q=\mu(R-I d)$
The matrix $Q$ is the instantaneous rate matrix ruling the Markov process.

## Nucleotide substitution models

Each evolutionary model assumes meaningful constraints on the set of substitution probabilities or rates:

- Algebraic models: Constraints on probabilities $(M)$.
- Continuous-time models: Constraints on rates $(Q)$.

A matrix structure provides two different but related models.

## Embedding Problem (Related questions)

- Which Markov matrices are rejected/considered for each approach?
- Are we allowed to concatenate homogeneous processes?


## Drawbacks

- Algebraic models consider unrealistic matrices.

$$
\left(\begin{array}{llll}
0 & 0 & 0 & 1 \\
0 & 0 & 1 & 0 \\
0 & 1 & 0 & 0 \\
1 & 0 & 0 & 0
\end{array}\right)
$$

- The product of embeddable matrices is not necessarily an embeddable matrix.
- There are Markov matrices close to Id that are not the exponential of any rate matrix.

$$
\left(\begin{array}{cccc}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1-\varepsilon_{1} & \varepsilon_{1} \\
0 & \varepsilon_{2} & 0 & 1-\varepsilon_{2}
\end{array}\right)
$$

## Rate identifiability

If the determinant is small enough there might be more than one generator:

$$
Q 1=\left(\begin{array}{cccc}
-\pi & 0 & 0 & \pi \\
0 & -\pi & \pi & 0 \\
\pi & 0 & -\pi & 0 \\
0 & \pi & 0 & -\pi
\end{array}\right) \quad Q_{2}=\left(\begin{array}{cccc}
-\pi & 0 & \pi & 0 \\
0 & -\pi & 0 & \pi \\
\pi & 0 & -\pi & 0 \\
0 & \pi & 0 & -\pi
\end{array}\right) .
$$

## Identifiability Problem

Given an embeddable Markov matrix, is there a unique Markov generator? If not, how many Markov generators does it admit?

## Enumerating all the logarithms of a matrix

All the logarithms of a (non-singular) diagonalizable matrix are given by choosing a diagonalizing basis and a determination of the logarithm for each of its eigenvalues:

## Theorem

Given a non-singular matrix $M=P \operatorname{diag}\left(\lambda_{1}, \lambda_{2}, \ldots, \lambda_{n}\right) P^{-1}$, then any solution $Q$ of the equation $M=e^{Q}$ can be expressed as:

$$
Q=(P A) \operatorname{diag}\left(\log _{k_{1}}\left(\lambda_{1}\right), \log _{k_{2}}\left(\lambda_{2}\right), \ldots, \log _{k_{n}}\left(\lambda_{n}\right)\right)(P A)^{-1}
$$

for some $k_{1}, k_{2}, \ldots, k_{n} \in \mathbb{Z}, A \in \operatorname{Comm}^{*}\left(\operatorname{diag}\left(\lambda_{1}, \lambda_{2}, \ldots, \lambda_{n}\right)\right)$.

## The principal logarithm

Any non-singular matrix $A \in G L_{n}(\mathbb{R})$ has a unique logarithm, called the principal logarithm $\log (A)$, all of whose eigenvalues lie in the strip $\{z \in \mathbb{C} \mid-\pi<\operatorname{Im}(z) \leq \pi\}$.

- $\log (M)$ is real iff $M$ has no negative eigenvalues.
- $\log (M)$ is the only possible Markov generator if $M$ is close enough to Id.
Cuthbert(1972), Singer and Spilerman(1976), Israel et al.,(2001)


## Theorem (Singer and Spilerman(1976))

Solution to the embedding problem and the rate identifiability problem for Markov matrices with different real eigenvalues.

## Embeddability of $n \times n$ Markov matrices

## Lemma

Let $Q$ be a rate matrix. Then for any eigenvalue $\lambda \in \sigma(Q)$ we have

$$
|\operatorname{Im}(\lambda)| \leq \min \left\{\sqrt{2 \operatorname{tr}(Q) \operatorname{Re}(\lambda)-(\operatorname{Re}(\lambda))^{2}},-\frac{\operatorname{Re}(\lambda)}{\tan (\pi / n)}\right\} .
$$

We can bound the number of real logarithms with rows summing to zero in terms of the eigenvalues and the determinant of $M$.

## Theorem

(Algorithmic) Solution to the embedding problem for a dense subset of $n \times n$ Markov matrices (for any n).

MC, JFS and JRL The embedding problem for Markov matrices. arXiv:2005.00818

## Embeddability of $4 \times 4$ Markov matrices

## Theorem

Let $M=P \operatorname{diag}\left(1, \lambda_{1}, \lambda_{2}, \lambda_{3}\right) P^{-1}$, be a Markov matrix with different eigenvalues $\lambda_{1} \in \mathbb{R}, \lambda_{2}, \lambda_{3} \in \mathbb{C}$.

$$
\begin{aligned}
& \lambda_{2}, \lambda_{3} \in \mathbb{R} \text { : Let } V \text { be the zero matrix and } \mathcal{L}=\mathcal{U}=0 . \\
& \lambda_{2}, \lambda_{3} \notin \mathbb{R} \text { : Take } V=P \operatorname{diag}(0,0,2 \pi i,-2 \pi i) P^{-1} \\
& \mathcal{L}:=\max _{i \neq j, v_{i, j}>0}\left\lceil-\frac{\log (M)_{i, j}}{V_{i, j}}\right\rceil, \mathcal{U}:=\min _{i \neq j, v_{i, j}<0}\left\lfloor-\frac{\log (M)_{i, j}}{V_{i, j}}\right\rfloor .
\end{aligned}
$$

$M$ is embeddable if and only if

- $\lambda_{i} \notin \mathbb{R}_{\leq 0}$,
- $\left\{(i, j): i \neq j, \quad V_{i, j}=0\right.$ and $\left.\log (M)_{i, j}<0\right\}=\emptyset$,
- $\mathcal{L} \leq \mathcal{U}$.

The Markov generators of $M$ are $\log (M)+k V$ with $k \in[\mathcal{L}, \mathcal{U}]$.

## Embeddability of $4 \times 4$ Markov matrices

## Sketch of proof

$\lambda_{2}, \lambda_{3} \in \mathbb{R}$
$M$ is embeddable $\Leftrightarrow \log (M)$ is a rate (even if $\lambda=1$ ).
$\lambda_{2}, \lambda_{3} \notin \mathbb{R}$
All the real logarithms with rows summing to 0 can be written as $\log _{k}(M):=\log (M)+k \cdot V$ for some $k \in Z$.
$\log _{k}(M)$ is a rate matrix if and only if $N=\emptyset$ and $\mathcal{L} \leq k \leq \mathcal{U}$.

MC, JFS and JRL The embedding problem for Markov matrices. arXiv:2005.00818

## Embeddability of $4 \times 4$ Markov matrices

## Theorem

For all $k \in \mathbf{Z}$, there is a non-empty open set of embeddable Markov matrices whose unique Markov generator is $\log _{k}$.

MC, JFS and JRL An open set of $4 \times 4$ embeddable matrices whose principal logarithm is not a Markov generator. To appear in Linear and Multilinear Algebra.

In particular, there is a non-empty Euclidean open set of $4 \times 4$ Markov matrices that are embeddable and whose principal logarithm is not a rate matrix.

## Embeddability of $4 \times 4$ Markov matrices

Special case: $M=P \operatorname{diag}(1, \lambda, \mu, \mu) P^{-1}$ with $\lambda \geq 0, \mu \neq 0, \lambda$.

- Define $Q_{k}(x, y, z)=L+(2 \pi k+\operatorname{Arg} \mu) V(x, y, z)$, where

$$
\begin{aligned}
& L=P \operatorname{diag}(0, \log (\lambda), \log |\mu|, \log |\mu|) P^{-1} \\
& V(x, y, z)=P \operatorname{diag}\left(0,0,\left(\begin{array}{cc}
-y & x \\
-z & y
\end{array}\right)\right) P^{-1} .
\end{aligned}
$$

- $\mathcal{P}_{k}=\left\{(x, y, z) \in \mathbb{R}^{3}: Q_{k}(x, y, z)\right.$ is a rate matrix $\}$.

$$
\mathcal{V}=\left\{(x, y, z) \in \mathbb{R}^{3}: x>0, z>0 \text { and } x z-y^{2}=1\right\}
$$



## Embeddability of $4 \times 4$ Markov matrices

Special case: $M=P \operatorname{diag}(1, \lambda, \lambda, \lambda) P^{-1}$ with $\lambda \in \mathbb{R}$.

- $\log (M)=\frac{-\log (\lambda)}{1-\lambda}(M-I d)$.
- The following are equivalent:
i) $M$ is embeddable.
ii) $\operatorname{det}(M)>0$.
iii) $\log (M)$ is a rate matrix.

Special case: $M$ does not diagonalize. $M$ embeddable $\Leftrightarrow \log (M)$ is a rate matrix.

## Evolutionary Models: Kimura models

## Definition

Kimura 3-parameter model (K3P) assign probabilities/rates depending on the types of the substitution.


$$
\left(\begin{array}{llll}
\cdot & b & c & d \\
b & \cdot & d & c \\
c & d & \cdot & b \\
d & c & b & \cdot
\end{array}\right)
$$

- K2P model: $c=d$.
- JC model: $b=c=d$.


## Embedding problem: Kimura 3-parameter model

## Theorem

Let $M$ be a Markov K3ST matrix with eigenvalues $1, x, y, z$.

- If all eigenvalues are positive, then

$$
M \text { is embeddable } \Leftrightarrow x \geq y z, y \geq x z, z \geq x y .
$$

- If $M$ has a negative eigenvalue, say $x$, then
$M$ is embeddable $\Leftrightarrow x$ has algebraic multiplicity 2, and

$$
x^{2} \leq y \leq e^{-2 \pi}
$$

Relative volume of K3P embeddable matrices $=0.09375$.

JRL and JFS, Embeddability of Kimura 3ST Markov matrices, Journal of theoretical biology 445)
D. Kosta and K. Kubjas. Geometry of time-reversible group-based models.

## Embedding problem: Kimura 2-parameter model

## Theorem

$M=\left(\begin{array}{llll}\cdot & b & c & c \\ b & \cdot & c & c \\ c & c & \cdot & b \\ c & c & b & \cdot\end{array}\right)$
$\square 1$ generator
$\square \infty$ generators


Relative volume of K2P embeddable matrices $=\frac{\left(1+e^{-3 \pi}\right)}{3}$.

MC, JFS and JRL Embeddability and rate identifiability of Kimura 2ST Markov matrices, Journal of Mathematical Biology Nov-2019.

## Some other nucleotide substitution models

## Definition

The strand symmetric model (SSM) takes into account the double strand structure of DNA ( Watson-Crick base pairing A-T, C-G ),

$$
\left(\begin{array}{llll}
\cdot & b & c & d \\
e & \cdot & g & h \\
h & g & \cdot & e \\
d & c & b & \cdot
\end{array}\right)
$$

## Definition

The General Markov model (GM) allows any $4 \times 4$ Markov/rate matrix a nucleotide substitution process.

## Embedding problem: Nucleotide substitution models

## Corollary

Percentage of embeddable matrices w.r.t all $4 \times 4$ Markov matries (GM model), the strand symmetric model (SSM), the K3P model and its submodels.

| Model | Dimension | Embeddable |
| :---: | :---: | :---: |
| JC | 1 | $75 \%$ |
| K2P | 2 | $33.336 \ldots \%$ |
| K3P | 3 | $9.375 \%$ |
| SSM | 6 | $\sim 1.745 \%$ |
| GM | 12 | $\sim 0.05774 \%$ |

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