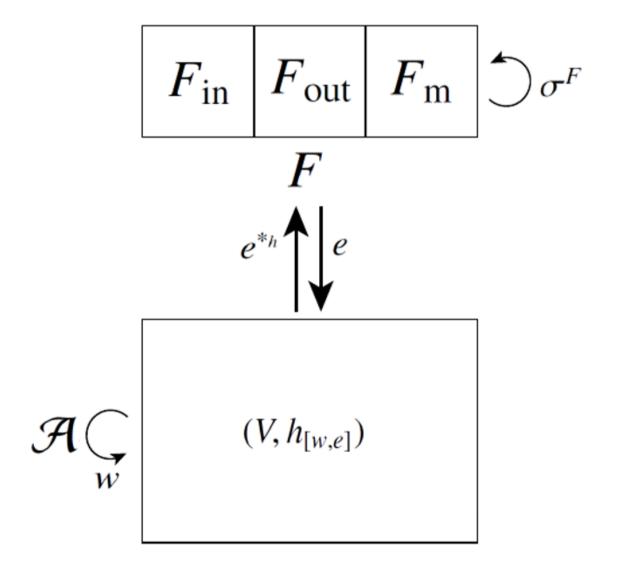
Siu Cheong Lau

Quiver representation emerges from Lie theory and mathematical physics. Its simplicity and beautiful theory have attracted a lot of mathematicians and physicists. In this talk, I will explain localizations of a quiver algebra, and the relations with SYZ and noncommutative mirror symmetry. I will also explore the applications of quivers to computational models in machine learning.

- 1. Motivation: sheaves \leftrightarrow quiver representations
- 2. SYZ mirrors and quivers
- 3. Framed quivers as computers



One important source: quiver resolution and quiver gauge theory.

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For a local Calabi-Yau singularity X = \operatorname{Spec} R, let Y be a crepant resolution (f^*\omega_X = \omega_Y).

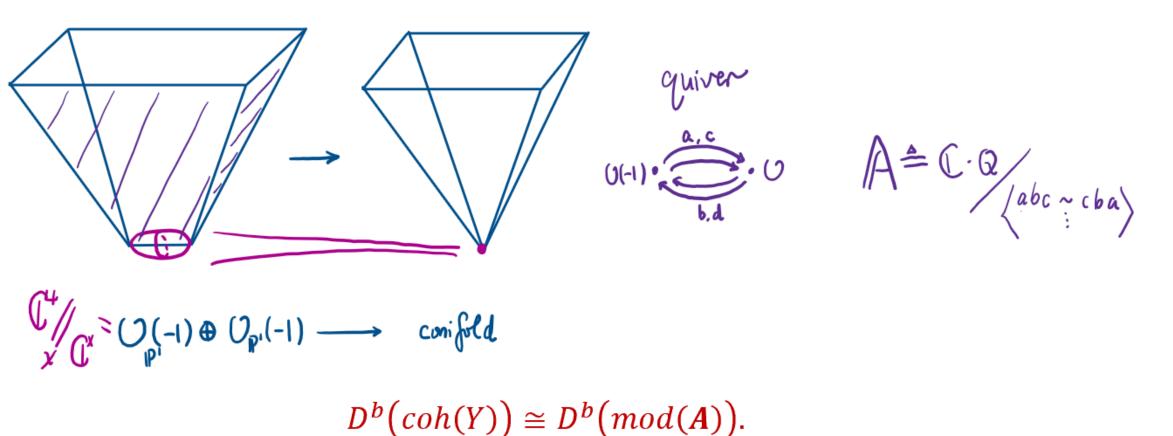
Van den Bergh has formulated quiver algebra A, called noncommutative crepant resolution, such that D^b(\operatorname{coh}(Y)) \cong D^b(\operatorname{mod}(A)).
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 $A := \operatorname{End}_R(M)$ where M: a reflexive R-module $(M^{**} \cong M)$.

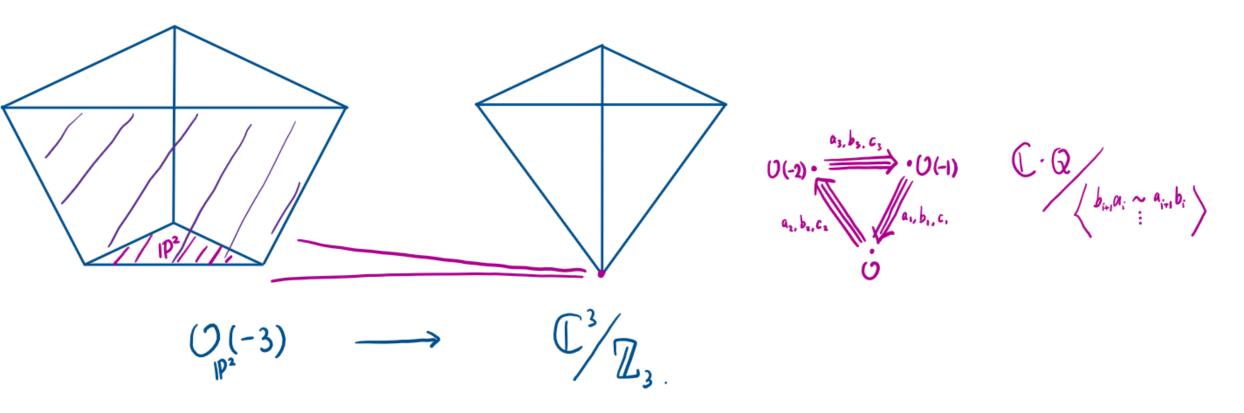
Douglas-Moore use quiver to encode a system of D-branes wrapping a Calabi-Yau threefold singularity.

Quiver is also useful in studying noncommutative deformations [**Donovan-Wemyss**].

Ex. conifold singularity $\{y_0w_1 = y_1w_0\}$. Crepant resolution:



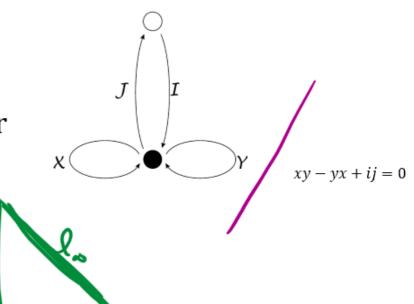
Ex. Orbifold $\mathbb{C}^3/\mathbb{Z}_3$. Crepant resolution:



Another important source for **sheaf** ↔ **quiver representation**: **ADHM quiver [Atiyah-Drinfeld-Hitchin-Manin, Donaldson, Nakajima]**.

Yang-Mills instantons over \mathbb{S}^4 $(F_A = -*F_A)$

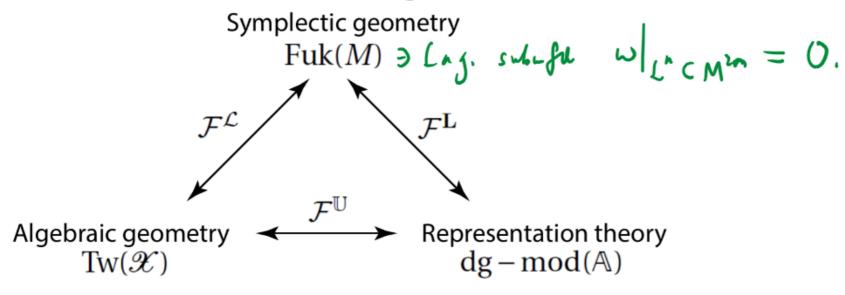
- \leftrightarrow stable quiver representations over ADHM quiver
- \leftrightarrow framed torsion-free sheaves over $(\mathbb{P}^2, l_{\infty})$. (multiplication by $O_{\chi} \{0\}$ on E_{χ} is injective)



Generalized to ALE surfaces $\widehat{\mathbb{C}^2/\Gamma}$ [Kronheimer-Nakajima].

We will use mirror symmetry to systematically construct the algebro-geometric correspondence: **sheaf** ↔ **quiver representation**.

Theorem: there exists a triangle of functors:



- $\mathcal{F}^{\mathcal{L}}$ is SYZ mirror functor.
- \bullet $\mathcal{F}^{\mathbf{L}}$ is quiver mirror functor.
- \mathcal{F}^{U} is constructed from isomorphism $\mathcal{L} \leftrightarrow \mathbf{L}$.

SYZ mirror and quiver

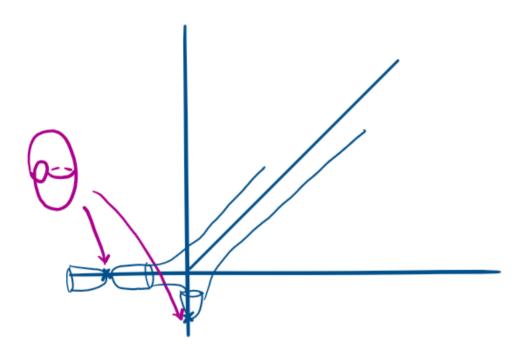
- Mirror symmetry is duality symplectic $(M, \omega) \leftrightarrow \text{complex } (X, J)$.
- Found by string theorists in the 90's.
- Powerful prediction of Gromov-Witten invariants proved by [Givental] and [Lian-Liu-Yau].
- Homological mirror symmetry [Kontsevich]: $DFuk(M) \cong DCoh(X)$.
- Mirror symmetry is T-duality [Strominger-Yau-Zaslow].

$$T \rightarrow M \longrightarrow X \leftarrow T = \{flit \ ull\} - connection on T\}$$

$$= \{imaginary \ defunction \ of \ T\}.$$

$$B$$

SYZ singular fibers are the sources of quantum corrections, which form wall-crossing and scattering [Kontsevich-Soibelman, Gross-Siebert, Auroux, Gross-Hacking-Keel...]

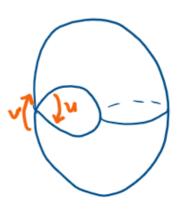


We glue **deformation spaces of SYZ singular fibers** to construct the mirror.

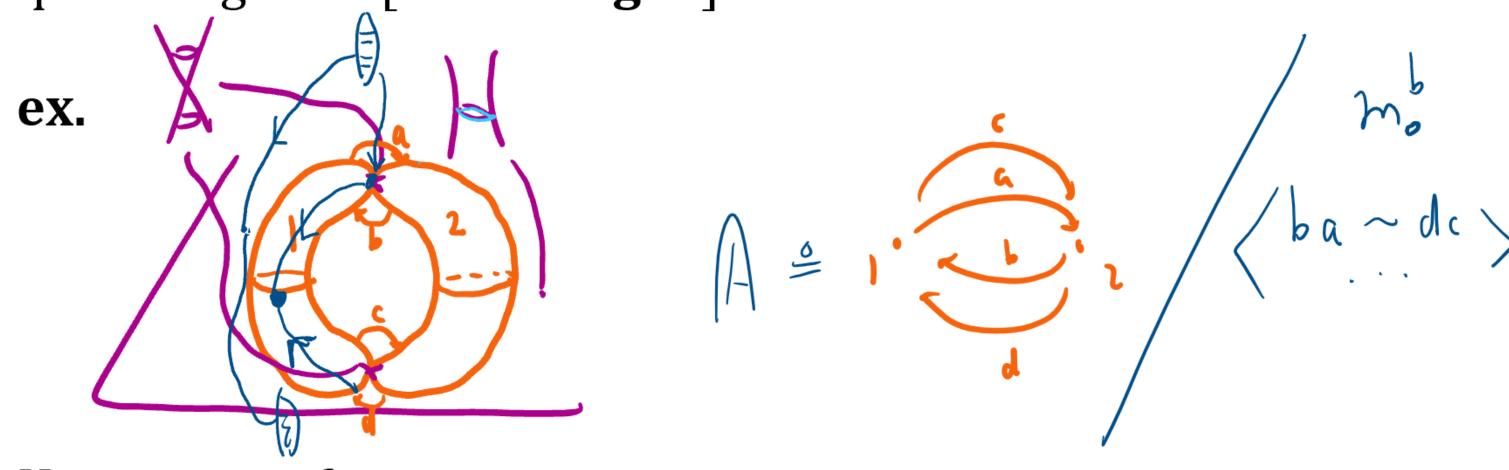
[Cho-Hong-L., Hong-L.-Kim, L.-Nan-Tan]

ex. Deformation space of the nodal sphere is

$$\left(\left(u,v \right) \left(\left(uv-1 \right)^{-1} \right) \right)$$



Note: generally, SYZ singular fiber corresponds to quiver algebra! [Cho-Hong-L.]



Have mirror functor

Gluing quiver algebras together produce a quiver stack.

(Algebroid stack was defined by [Kashiwara; O'brian-Toledo-Tong; D'Agnolo-Polesello; Bressler-Gorokhovsky-Nest-Tsygan; Block-Holstein-Wei...])

Def. A quiver stack consists of the following:

- (1) An open cover $\{U_i : i \in I\}$ of B.
- (2) A sheaf of algebras \mathcal{A}_i over each U_i , coming from localizations of a quiver algebra $\mathcal{A}_i(U_i) = \mathbb{C}Q^{(i)}/R^{(i)}$.
- (3) A sheaf of representations G_{ij} of $Q_V^{(j)}$ over $\mathcal{A}_i(V)$ for every i, j and $V \subseteq U_{ij}$.
- (4) An invertible element $c_{ijk}(v) \in \left(e_{G_{ij}(G_{jk}(v))} \cdot \mathcal{A}_i(U_{ijk}) \cdot e_{G_{ik}(v)}\right)^{\times}$ for every i, j, k and $v \in Q_0^{(k)}$, that satisfies
- (2.13) $G_{ij} \circ G_{jk}(a) = c_{ijk}(h_a) \cdot G_{ik}(a) \cdot c_{ijk}^{-1}(t_a)$ such that for any i, j, k, l and v,

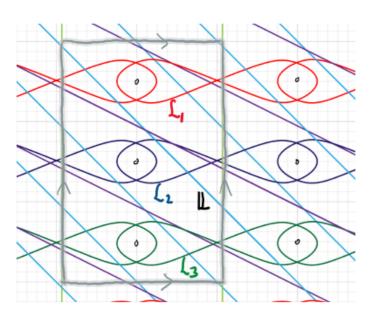
(2.14)
$$c_{ijk}(G_{kl}(v))c_{ikl}(v) = G_{ij}(c_{jkl}(v))c_{ijl}(v).$$
 In this paper, we always set $G_{ii} = \operatorname{Id}, c_{jjk} \equiv 1 \equiv c_{jkk}.$

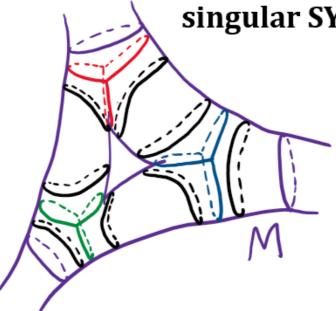
 c_{ijk} is called gerbe data (which is necessary for gluing quivers with different number of vertices).

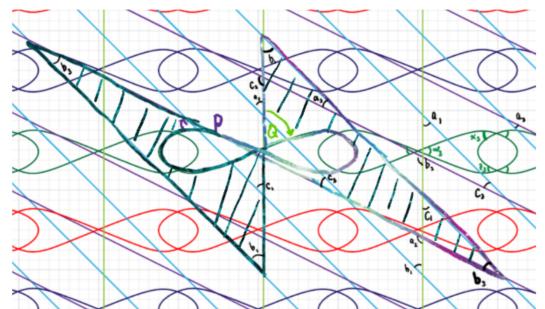
The notion enables us to glue generic SYZ fibers with singular Lagrangians via quasi-isomorphisms in the Fukaya category.

ex. Construction of $K_{\mathbb{P}^2}$ and quiver from mirror curve.

Seidel Lagrangians replacing the singular SYZ fibers.







Isomorphisms
$$(L_{o},b_{o}) \sim (L_{i},b_{i})$$
:
 $A_{03} = Q$;

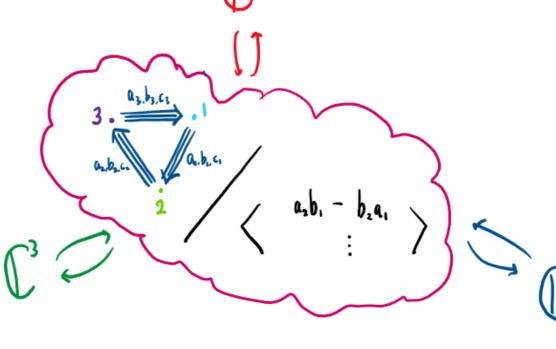
$$\mathsf{d}_{03} = \mathsf{Q} \; ;$$

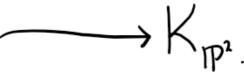
Theorem. [L.-Nan-Tan] There exists a quiver stack $\hat{\mathcal{Y}}$ such that α_{0j} , α_{j0} satisfy the isomorphism equations

$$m_1^{\hat{\mathcal{Y}}, \mathcal{E}_j, \mathcal{E}_k}(\alpha_{jk}) = 0;$$

$$m_2^{\hat{\mathcal{Y}}, \mathcal{E}_j, \mathcal{E}_k, \mathcal{E}_j}(\alpha_{jk}, \alpha_{kj}) = \mathbf{1}_{L_j}.$$

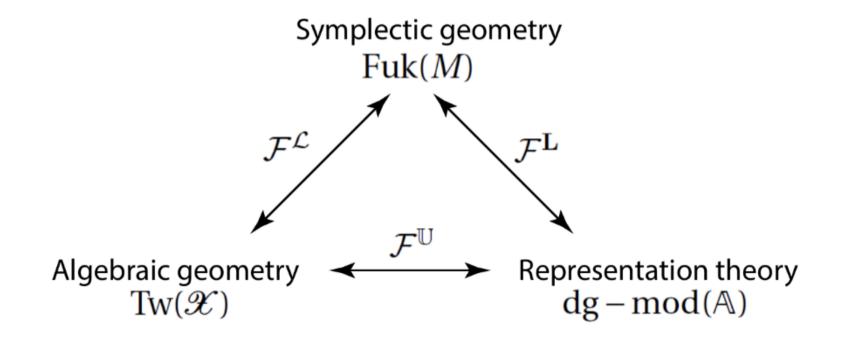
Such a method helps us to glue three non-intersecting SYZ fibers together via a middle agent!





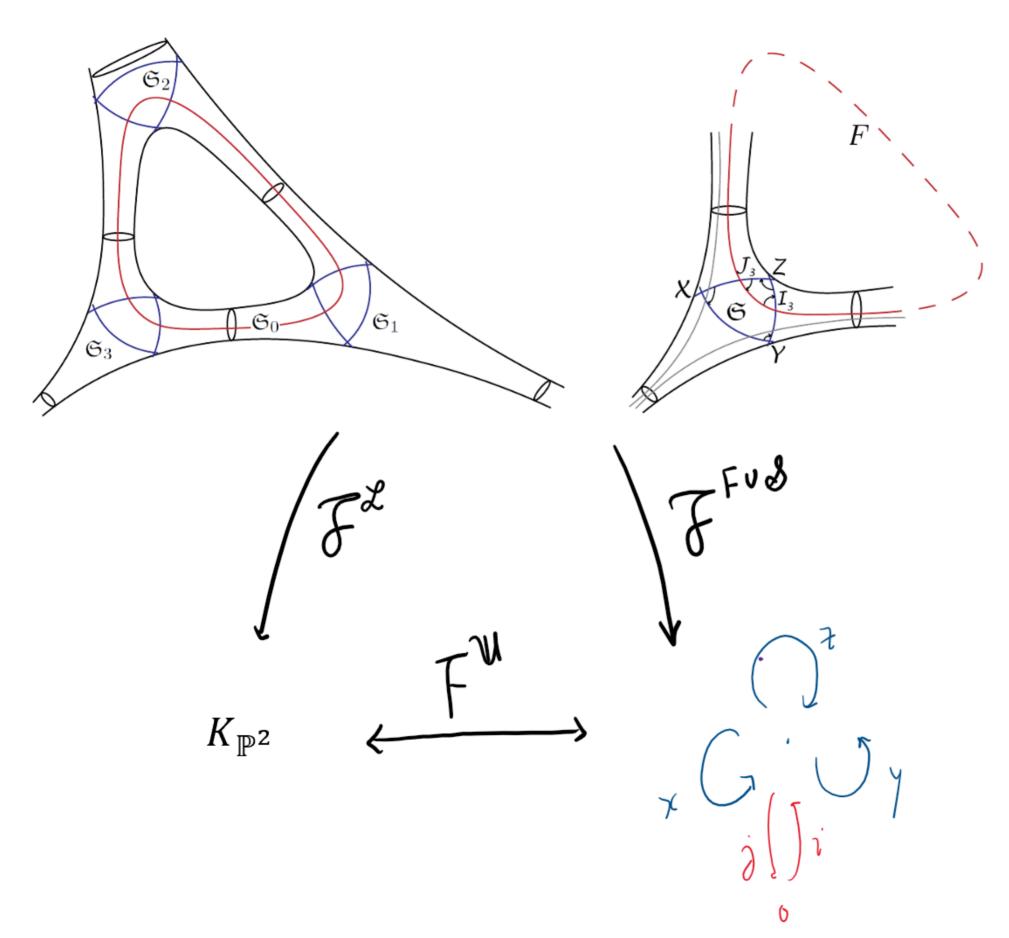
Conclusion:

- Have mirror functor $\mathcal{F}^{\mathcal{L}}$: $Fuk(M) \to Tw(X)$ by gluing singular SYZ fibers together.
- Have mirror functor $\mathcal{F}^{(L,b)}$: $Fuk(M) \to Mod(Q)$ by a single immersion L and its deformations (from a Lagrangian skeleton of M).
- $U := \mathcal{F}^{\mathcal{L}}(\boldsymbol{L}, \boldsymbol{b})$ gives $\mathcal{F}^{U} = \operatorname{Hom}_{\operatorname{Tw}(X)}(U, -) : Tw(X) \to Mod(Q)$.



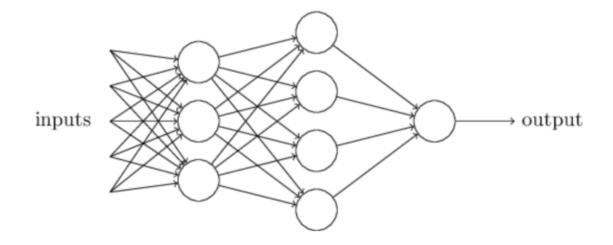
Ongoing work:

Use framed Lagrangian $F \cup S$ to produce the ADHM quiver and sheaves.



Quivers and machine learning

Remarkably, quiver representation is the key object in Deep learning.



Fix $\gamma \in \mathbb{C}Q$ that starts and ends with i_{in} , i_{out} .

Have a canonical linear function

 $L_{\gamma,w}: V_{i_{\text{in}}} \to V_{i_{\text{out}}}$ associated to each $w \in R(Q)$, by composing arrow linear maps along γ .

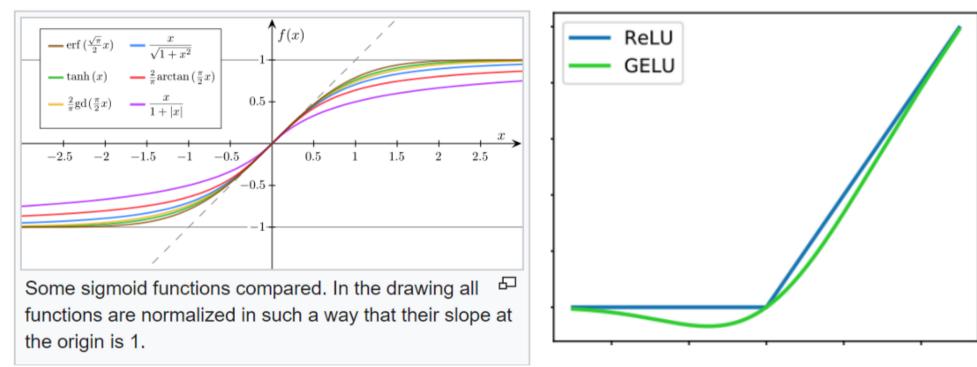
Representation learning:

Given $K \subset V_{i_{\text{in}}}$ and a continuous function $f: K \to V_{i_{\text{out}}}$ (statistically given), minimize the cost function $\left|L_{\gamma,w} - f\right|^2: R(Q) \to \mathbb{R}$ by taking a stochastic gradient descent in R(Q).

 \Rightarrow quiver representation that gives the best linear approximation.

Insight from neural network:

to get non-linear approximation, introduce non-linear 'activation functions' at vertices.

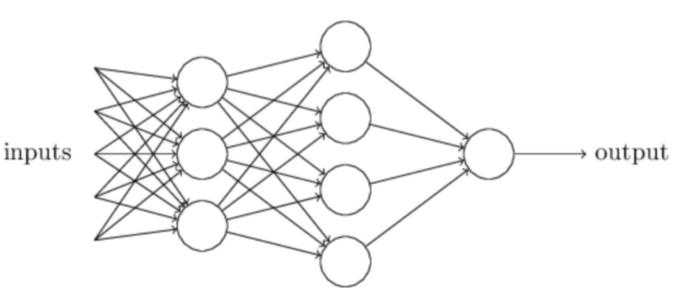


Compose with these activation functions and obtain **network function**

$$f_{\widetilde{\gamma},w}: V_{i_{\text{in}}} \to V_{i_{\text{out}}}$$

for every $w \in \text{Rep}(Q)$.

Do not occur in usual quiver theory.



We want to work with moduli space rather than the vector space R(Q) of representations.

$$M(Q) \coloneqq [R(Q)/G]$$

where

$$G = \prod_{i \in Q_0} \mathrm{GL}(V_i) \,.$$

[Mumford; Kings]

 $\{\theta - \text{semistable points in } R(Q)\}//G$.

GIT or slope stability: choose weights $\theta \in (\mathbb{Z}^{Q_0})^*$.

Rep.
$$V$$
 is θ -semi-stable if $\theta\left(\overline{\dim V'}\right) \leq \theta\left(\overline{\dim V}\right)$ for $V' \subset V$.

(Can also be understood via symplectic quotient.)

Obstacles of running deep learning over M(Q):

 $L_{\widetilde{\gamma},w}$ is composed with activation functions $\sigma: V_i \to V_i$, which are NOT G-equivariant: $\sigma(g \cdot v) \neq g \cdot \sigma(v)$.

This motivates us to use **framed** quiver representations

[Nakajima; Crawley-Boevey; Reineke].

Framed quiver representation:

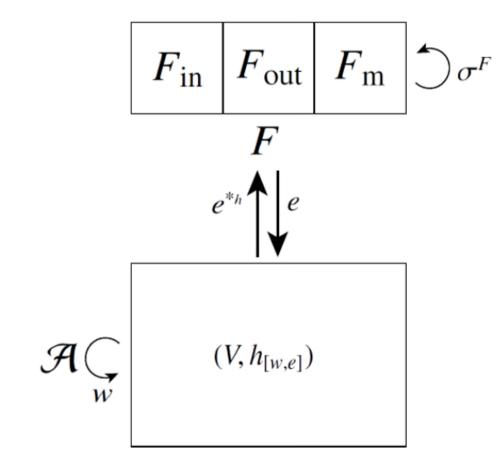
usual quiver representation (linear maps associated to arrows)

together with linear maps $e_i: \mathbb{C}^{n_i} \to V_i$ (called framing).

$$R^{\mathrm{fr}} \coloneqq \bigoplus_{a \in Q_1} \mathrm{Hom}(V_{t(a)}, V_{h(a)}) \oplus \bigoplus_{i \in Q_0} \mathrm{Hom}(\mathbb{C}^{n_i}, V_i) \ni (w, e).$$

$$\mathcal{M}^{\mathrm{fr}} \coloneqq \{ \text{stable points in } R^{\mathrm{fr}} \} / G.$$

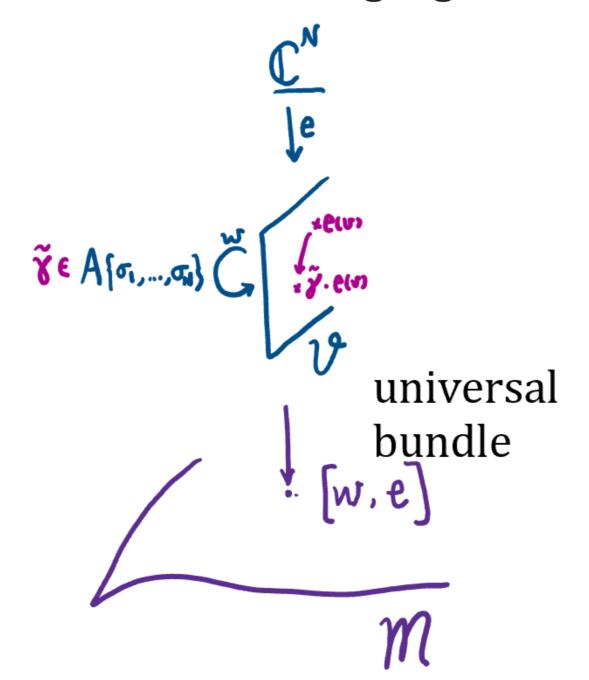
Think of V_i as state spaces; \mathbb{C}^{n_i} as spaces for input, output or memory.



Key: put the activation functions σ on the framing, rather than on the state spaces V.

Moreover, the moduli space has universal bundles $\mathcal{V}_i \to \mathcal{M}^{\mathrm{fr}}$. Each arrow a gives a vector-bundle map $\mathcal{V}_{t(a)} \to \mathcal{V}_{h(a)}$.

Using these, together with metric, can make well-defined learning algorithm over the quiver moduli.



Fix

- a graph Q,
- input and output vertices i_{in} , i_{out} ,
- the representation dimension vector,
- the framing $e_i: F_i \to V_i$,
- Non-linear functions $\sigma_i: F_i \to F_i$,
- the "algorithm" $\tilde{\gamma} \in \mathbb{C}\hat{Q}\{\sigma_1, ..., \sigma_N\}$,

Compose

arrow maps $\mathcal{V}_{t(a)} \to \mathcal{V}_{h(a)}$, framing maps $e_i \colon \mathbf{F}_i \to \mathcal{V}_i$, their metric adjoints $e_i^* \colon \mathcal{V}_i \to \mathbf{F}_i$, and $\sigma_i \colon F_i \to F_i$, get a machine function $f_{\widetilde{\gamma}} \colon V_{i_{\mathrm{in}}} \to V_{i_{\mathrm{out}}}$ over $\mathbf{\mathcal{M}}^{\mathrm{fr}}$.

Ex. A_n -quiver.

$$f_{\widetilde{\gamma}} = s_{n-1} \circ e^{\text{out}^*} \circ \left(w_{n-1} \circ \left(\dots \circ e^{(1)} \circ s_1 \circ e^{(1)^*} \circ \left(w_1 \circ e^{\text{in}} + b^{(1)} \right) \dots \right) + b^{(n-1)} \right).$$

To run the algorithm over $\mathcal{M}^{\mathrm{fr}}$, need

- (1) **vector-bundle metric** H_i on universal bundle V_i ;
- (2) Metric $h_{\mathcal{M}^{fr}}$ on \mathcal{M}^{fr} .

Thm.

Fix $i \in Q_0$.

• $H_i: R^{\mathrm{fr}} \to \mathrm{End}(\mathbb{C}^{d_i})$,

$$(w,e) \mapsto \left(\sum_{h(\gamma)=i} (w_{\gamma}e_{t(\gamma)})(w_{\gamma}e_{t(\gamma)})^*\right)^{-1}$$

gives a well-defined metric on $\mathcal{V}_i \to \mathcal{M}$.

• Moreover, assuming Q has no oriented cycle, the Ricci curvature $\sqrt{-1}\sum_i\partial\bar{\partial}\log\det H_i$ of the resulting metric on $\bigotimes_{i\in Q_0}U_i$ defines a Kaehler metric on $\mathcal{M}^{\mathrm{fr}}$.

Moreover, can uniformize with the original Euclidean setup and hyperbolic metric.

Assume $\vec{n} \ge \vec{d}$. Write the framing as $e^{(i)} = (\epsilon^{(i)} b^{(i)})$.

At points where $\epsilon^{(i)}$ is invertible, applying quiver automorphism $\Rightarrow \epsilon^{(i)} = \text{Id}$.

This gives a chart:

$$R_{\vec{n}-\vec{d},\vec{d}}(Q) \hookrightarrow \mathcal{M}_{\vec{n},\vec{d}}^{fr}(Q).$$

Uniformization gives a unified point of view towards $R_{\vec{n}-\vec{d},\vec{d}}(Q)$, $\mathcal{M}_{\vec{n},\vec{d}}^{\text{fr}}(Q)$, and $\mathcal{M}_{\vec{n},\vec{d}}^{-}(Q)$.

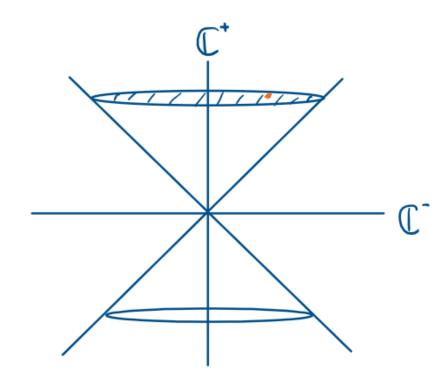
Ex. Hyperbolic disc $D \subset \mathbb{CP}^1$.

D, \mathbb{C} and \mathbb{CP}^1 can be uniformly understood:

$$\mathbb{CP}^1 = \{ \text{lines in } \mathbb{C}^2 \}.$$

If we equip \mathbb{C}^2 with the quadratic form $y^2 - x^2$, then $D = \{\text{spacelike lines in } \mathbb{C}^{1,1}\}.$

If we equip \mathbb{C}^2 with the quadratic form $H_0 = y^2$, then $\mathbb{C} = \{\text{spacelike lines in } (\mathbb{C}^2, H_0)\}.$



This is classically well understood for symmetric spaces, and $D \hookrightarrow \mathbb{CP}^1$ is known as **Borel embedding**.

We generalize this to framed quiver moduli.

Thm.

There exists spherical, hyperbolic, Euclidean moduli spaces \mathcal{M} , \mathcal{M}^- , \mathcal{M}^0 which can be interpolated by a family of metrics.

$$\left(\rho_i \begin{pmatrix} I_{d_i} & 0 \\ 0 & r \cdot I \end{pmatrix} \rho_i^* \right)^{-1}$$
.

$$M = 0$$

$$M < 0$$

Conclusion

- Quiver near algebras give a uniform setup for machine learning and quantum computing.
- Quiver gauge theory (resolution of local CY singularities) & ADHM provide correspondence between sheaves and quivers.
- The correspondence can be realized by mirror symmetry.
- We are using quivers as fundamental building blocks in both physical and computational models.

