

D-branes and Deep Learning

Theoretical and Computational Aspects in String Theory

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Conformal Symmetry and Geometry of the Worldsheet

Preliminary Concepts and Tools

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Orbifolds and Cosmological Toy Models

Null Boost Orbifold

Deep Learning the Geometry of String Theory

Machine Learning and Deep Learning

Machine Learning for String Theory

AI Implementations for Geometry and Strings

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Action Principle and Conformal Symmetry

Polyakov's Action

$$S_P[\gamma, X, \psi] = -\frac{1}{4\pi} \int_{-\infty}^{+\infty} d\tau \int_0^\ell d\sigma \sqrt{-\det \gamma} \gamma^{\alpha\beta} \left(\frac{2}{\alpha'} \partial_\alpha X^\mu \partial_\beta X^\nu + \psi^\mu \rho_\alpha \partial_\beta \psi^\nu \right) \eta_{\mu\nu}$$

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Symmetries:

- **Poincaré transf.** $X'^\mu = \Lambda^\mu_\nu X^\nu + c^\mu$
- **2D diff.** $\gamma'_{\alpha\beta} = (J^{-1})_{\alpha\beta}^{\lambda\rho} \gamma_{\lambda\rho}$
- **Weyl transf.** $\gamma'_{\alpha\beta} = e^{2\omega} \gamma_{\alpha\beta}$

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Conformal symmetry:

- **vanishing** stress-energy tensor: $\mathcal{T}_{\alpha\beta} = 0$
- **traceless** stress-energy tensor: $\text{tr } \mathcal{T} = 0$
- **conformal gauge** $\gamma_{\alpha\beta} = e^\Phi \eta_{\alpha\beta}$

Action Principle and Conformal Symmetry

Superstrings in D dimensions:

$$\mathcal{T}(z) = -\frac{1}{\alpha'} \partial X(z) \cdot \partial X(z) - \frac{1}{2} \psi(z) \cdot \partial \psi(z) \quad \Rightarrow \quad c = \frac{3}{2}D$$

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$(\lambda, 0) / (1 - \lambda, 0)$ Ghost System

Introduce anti-commuting (b, c) and commuting (β, γ) conformal fields:

$$S_{\text{ghost}}[b, c, \beta, \gamma] = \frac{1}{2\pi} \iint dz d\bar{z} (b(z) \bar{\partial} c(z) + \beta(z) \bar{\partial} \gamma(z))$$

where $\lambda_b = 2$ and $\lambda_c = -1$, and $\lambda_\beta = \frac{3}{2}$ and $\lambda_\gamma = -\frac{1}{2}$.

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Consequence:

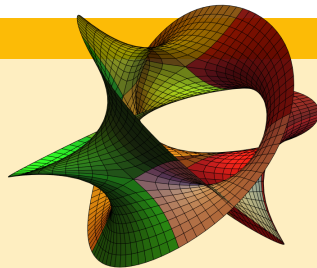
$$c_{\text{full}} = c + c_{\text{ghost}} = 0 \quad \Leftrightarrow \quad D = 10.$$

Extra Dimensions and Compactification

Compactification

$$\mathcal{M}^{1,9} = \mathcal{M}^{1,3} \otimes \mathcal{X}_6$$

- $\mathcal{X}_6$ is a **compact** manifold
- $N = 1$ **supersymmetry** is preserved in 4D
- algebra of $SU(3) \otimes SU(2) \otimes U(1)$ in arising **gauge group**

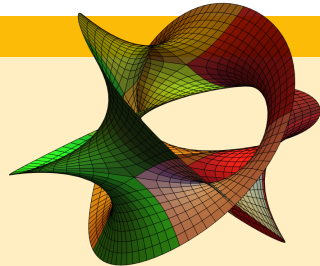


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Kähler manifolds (M, g) such that

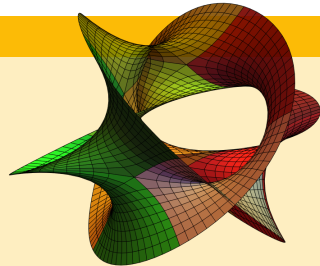
- $\dim_{\mathbb{C}} M = m$
- $\text{Hol}(g) \subseteq SU(m)$
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Characterised by Hodge numbers

$$h^{r,s} = \dim_{\mathbb{C}} H_{\bar{\partial}}^{r,s}(M, \mathbb{C})$$

counting the no. of harmonic (r, s) -forms.

D-branes and Open Strings

Polyakov's action naturally introduces Neumann b.c.:

$$\partial_\sigma X(\tau, \sigma) \Big|_{\sigma=0}^{\sigma=\ell} = 0$$

satisfied by **open and closed** strings living in D dimensions s.t. $\square X = 0$.

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T-duality

$$X(z, \bar{z}) = X(z) + \overline{X}(\bar{z}) \quad \xrightarrow{T} \quad X(z) - \overline{X}(\bar{z}) = Y(z, \bar{z}) = Y(z) + \overline{Y}(\bar{z})$$

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Resulting effect (repeated $p \leq D - 1$ times) leads to Dirichlet b.c.:

$$\partial_\sigma X^i(\tau, \sigma) \Big|_{\sigma=0}^{\sigma=\ell} = 0 \xrightarrow{T} \partial_\tau Y^i(\tau, \sigma) \Big|_{\sigma=0}^{\sigma=\ell} = 0 \quad \forall i = 1, 2, \dots, p$$

thus **open strings** can be **constrained** to $D(D - p - 1)$ -branes.

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Introducing Dp -branes breaks $\text{ISO}(1, D - 1) \rightarrow \text{ISO}(1, p) \otimes \text{SO}(D - 1 - p)$.

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Massless Spectrum (*irrep* of little group $\text{SO}(D-2)$)

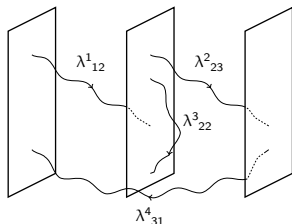
$$\mathcal{A}^\mu \leftrightarrow \alpha_{-1}^\mu |0\rangle \longrightarrow \begin{array}{ll} \mathcal{A}^A \leftrightarrow \alpha_{-1}^A |0\rangle, & A = 0, 1, \dots, p \\ \mathcal{A}^a \leftrightarrow \alpha_{-1}^a |0\rangle, & a = 1, 2, \dots, D-p-1 \end{array}$$

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Introducing **Chan-Paton factors** λ^r_{ij} , when branes are **coincident**:

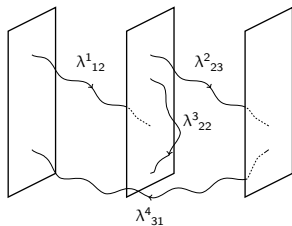
$$\bigoplus_{r=1}^N \text{U}_r(1) \longrightarrow \text{U}(N)$$

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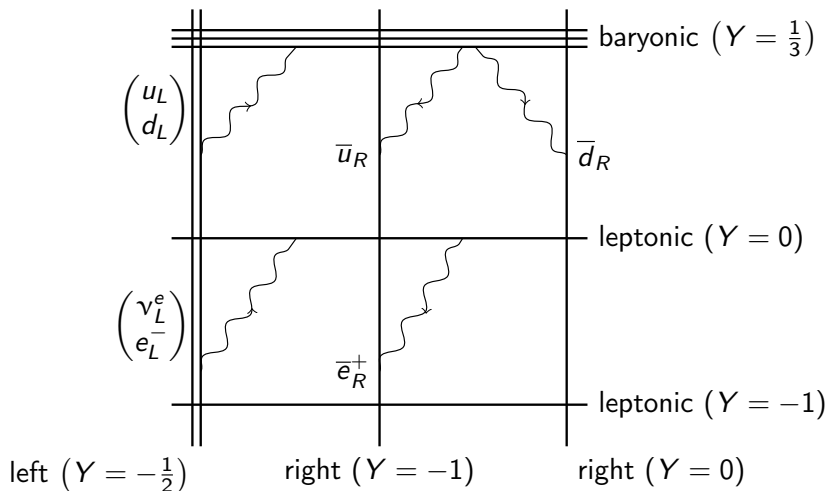


Introducing **Chan-Paton factors** λ^r_{ij} , when branes are **coincident**:

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Build gauge bosons, fermions and scalars.

Standard Model-like Scenarios



Intersecting D-branes

Consider N intersecting $D6$ -branes filling $\mathcal{M}^{1,3}$ and embedded in $\mathbb{R}^6$

Twist Fields Correlators

$$\left\langle \prod_{t=1}^{N_B} \sigma_{M_{(t)}}(x_{(t)}) \right\rangle = \mathcal{N} \left(\{x_{(t)}, M_{(t)}\}_{1 \leq t \leq N_B} \right) e^{-S_E(\text{cl}) \left(\{x_{(t)}, M_{(t)}\}_{1 \leq t \leq N_B} \right)}$$

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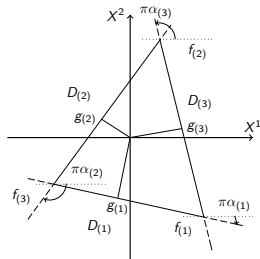
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D-branes in **factorised** internal space:

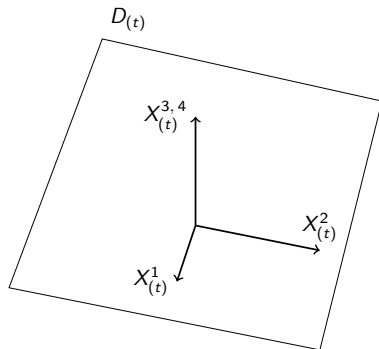
- **embedded as lines** in $\mathbb{R}^2 \times \mathbb{R}^2 \times \mathbb{R}^2$
- **relative rotations** are $\text{SO}(2) \simeq \text{U}(1)$ elements
- $S_E(\text{cl}) \left(\{x(t), M(t)\}_{1 \leq t \leq N_B} \right) \sim \text{Area} \left(\{f(t), R(t)\}_{1 \leq t \leq N_B} \right)$

SO(4) Rotations

Consider $\mathbb{R}^4 \times \mathbb{R}^2$ (focus on $\mathbb{R}^4$):

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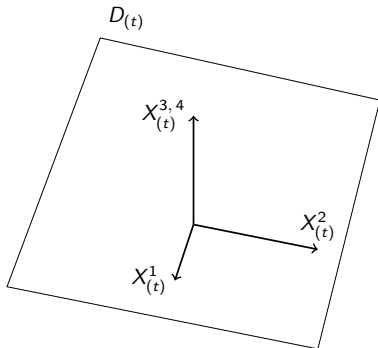
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$$(X_{(t)})^I = (R_{(t)})^I_J X^J - g_{(t)}^I$$

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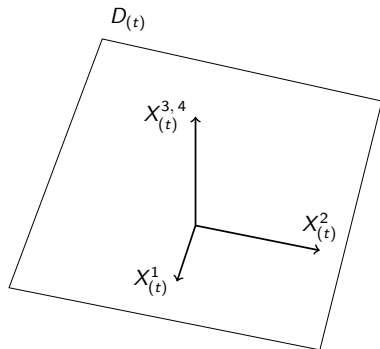
where

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$$[R_{(t)}] = \{R_{(t)} \sim \mathcal{O}_{(t)} R_{(t)}\}$$

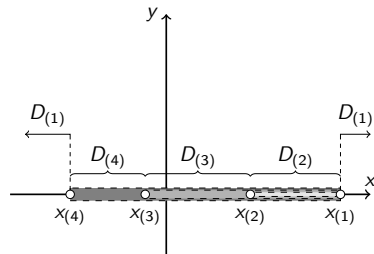
Boundary Conditions

What are the consequences for open strings?

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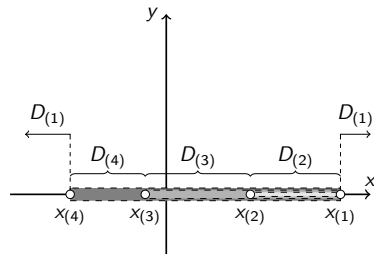
- consider $u = x + iy = e^{\tau_e + i\sigma}$ and $\bar{u} = u^*$
- let $x_{(t)} < x_{(t-1)}$ be the **worldsheet intersection points on real axis**
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Branch Cuts and Discontinuities for $x \in D_{(t)}$

$$\begin{cases} \partial_u X(x + i0^+) = U_{(t)} \cdot \partial_{\bar{u}} \bar{X}(x - i0^+) = \left[R_{(t)}^{-1} \cdot (\sigma_3 \otimes \mathbb{1}_2) \cdot R_{(t)} \right] \cdot \partial_{\bar{u}} \bar{X}(x - i0^+) \\ X(x_{(t)}, x_{(t)}) = f_{(t)} \end{cases}$$

Doubling Trick and Spinor Representation

Doubling Trick

$$\partial_z \mathcal{X}(z) = \begin{cases} \partial_u X(u) & \text{if } z \in \mathcal{H}_{>}^{(\bar{t})} \\ U_{(\bar{t})} \partial_{\bar{u}} \bar{X}(\bar{u}) & \text{if } z \in \mathcal{H}_{<}^{(\bar{t})} \end{cases} \Rightarrow \begin{aligned} \partial_z \mathcal{X}(x_{(t)} + e^{2\pi i} \delta_+) &= \mathcal{U}_{(t, t+1)} \partial_z \mathcal{X}(x_{(t)} + \delta_+), \\ \partial_z \mathcal{X}(x_{(t)} + e^{2\pi i} \delta_-) &= \tilde{\mathcal{U}}_{(t, t+1)} \partial_z \mathcal{X}(x_{(t)} + \delta_-), \end{aligned}$$

where $\mathcal{H}_{\gtrless}^{(t)} = \{z \in \mathbb{C} \mid \text{Im } z \gtrless 0 \text{ or } z \in D_{(t)}\}$ and $\delta_{\pm} = \eta \pm i0^+$.

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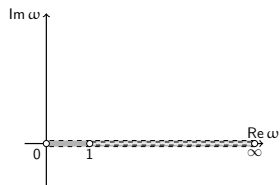
Use Pauli matrices $\tau = (i \mathbb{1}_2, \vec{\sigma})$:

$$\partial_z \mathcal{X}_{(s)}(z) = \partial_z \mathcal{X}'(z) \tau_I \Rightarrow \partial_z \mathcal{X}(x_{(t)} + e^{2\pi i} \delta_{\pm}) = \overset{(\sim)}{\mathcal{L}}_{(t, t+1)} \partial_z \mathcal{X}(x_{(t)} + \delta_{\pm}) \overset{(\sim)}{\mathcal{R}}_{(t, t+1)}$$

where

$$\overset{(\sim)}{\mathcal{L}}_{(t, t+1)} \in \text{SU}(2)_L \quad \text{and} \quad \overset{(\sim)}{\mathcal{R}}_{(t, t+1)} \in \text{SU}(2)_R$$

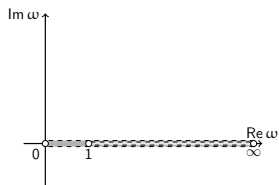
Hypergeometric Basis



Sum over all contributions:

$$\partial_z \mathcal{X}(z) = \sum_{l,r} c_{lr} (-\omega_z)^{A_{lr}} (1 - \omega_z)^{B_{lr}} B_{0,l}^{(L)}(\omega_z) \left(B_{0,r}^{(R)}(\omega_z) \right)^T$$

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Basis of Solutions

$$B_{0,n}(\omega_z) = \begin{pmatrix} 1 & 0 \\ 0 & K_n \end{pmatrix} \begin{pmatrix} \frac{1}{\Gamma(c_n)} {}_2F_1(a_n, b_n; c_n; \omega_z) \\ \frac{(-\omega_z)^{1-c_n}}{\Gamma(2-c_n)} {}_2F_1(a_n + 1 - c_n, b_n + 1 - c_n; 2 - c_n; \omega_z) \end{pmatrix}$$

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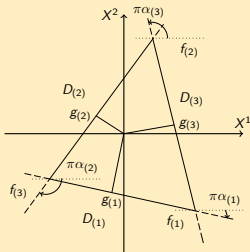
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Physical Interpretation



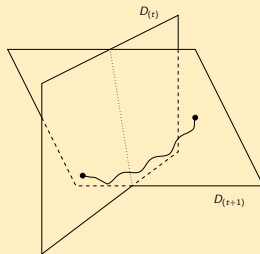
$$\begin{aligned}
 S_{\mathbb{R}^4} \Big|_{\text{on-shell}} &= \frac{1}{2\pi\alpha'} \sum_{t=1}^3 \left(\frac{1}{2} |g_{(t)}^\perp| |f_{(t-1)} - f_{(t)}| \right) \\
 &= \text{Area}(\{f_{(t)}\})
 \end{aligned}$$

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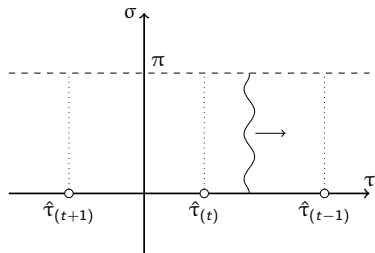
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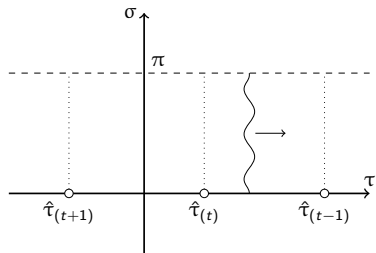
Fermions on the Strip



Action of Boundary Changing Operators

$$\begin{cases} \psi_-^i(\tau, 0) &= (R_{(t)})^I{}_J \psi_+^J(\tau, 0) \quad \text{for } \tau \in (\hat{\tau}_{(t)}, \hat{\tau}_{(t-1)}) \\ \psi_-^I(\tau, \pi) &= -\psi_+^I(\tau, \pi) \quad \text{for } \tau \in \mathbb{R} \end{cases}$$

Fermions on the Strip



Action of Boundary Changing Operators

$$\begin{cases} \psi_-^i(\tau, 0) &= (R_{(t)})^i_j \psi_+^j(\tau, 0) \quad \text{for } \tau \in (\hat{\tau}_{(t)}, \hat{\tau}_{(t-1)}) \\ \psi_-^i(\tau, \pi) &= -\psi_+^i(\tau, \pi) \quad \text{for } \tau \in \mathbb{R} \end{cases}$$

Stress-energy Tensor

$$\mathcal{T}_{\pm\pm}(\xi_{\pm}) = -i \frac{T}{4} \psi_{\pm, \mu}^*(\xi_{\pm}) \overleftrightarrow{\partial} \psi_{\pm}^{\mu}(\xi_{\pm}) \quad \Rightarrow \quad \begin{cases} \dot{H}(\tau) &= 0 \Leftrightarrow \tau \in (\tau_{(t)}, \tau_{(t-1)}) \\ \dot{P}(\tau) &\neq 0 \end{cases}$$

Conserved Product and Operators

Expand on a basis of solutions

$$\psi_{\pm}(\xi_{\pm}) = \sum_{n=-\infty}^{+\infty} b_n \psi_n(\xi_{\pm}) \quad \Rightarrow \quad \Psi(z) = \begin{cases} \psi_{E,+}(u) & \text{if } z \in \mathcal{H}_{>}^{(\bar{t})} \\ \psi_{E,-}(u) & \text{if } z \in \mathcal{H}_{<}^{(\bar{t})} \end{cases}$$

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Conserved Product and Dual Basis

$$\langle\langle {}^*\psi_n, \psi_m \rangle = 2\pi\mathcal{N} \oint \frac{dz}{2\pi i} {}^*\Psi_n {}^*\Psi_m = \delta_{n,m} \quad \Rightarrow \quad \langle\langle {}^*\Psi_n^{(*)}, \Psi^{(*)} \rangle = b_n^{(\dagger)}$$

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Derive the algebra of operators:

$$[b_n, b_m^{\dagger}]_+ = \frac{2\mathcal{N}}{T} \langle\langle {}^*\Psi_n^*, \Psi_m^* \rangle\rangle$$

Twisted Complex Fermions

Consider the case $R_{(t)} = e^{i\pi\alpha_{(t)}} \in U(1)$:

$$\Psi(x_{(t)} + e^{2\pi i}\delta) = e^{i\pi\epsilon_{(t)}} \Psi(x_{(t)} + \delta)$$

where

$$\epsilon_{(t)} = \alpha_{(t+1)} - \alpha_{(t)} + \theta(\alpha_{(t)} - \alpha_{(t+1)} - 1) - \theta(\alpha_{(t+1)} - \alpha_{(t)} - 1)$$

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Basis of Solutions

$$\Psi_n(z; \{x_{(t)}\}) = \mathcal{N}_\Psi z^{-n} \prod_{t=1}^N \left(1 - \frac{z}{x_{(t)}}\right)^{n_{(t)} + \frac{\epsilon_{(t)}}{2}}$$

$$^*\Psi_n(z; \{x_{(t)}\}) = \frac{1}{2\pi\mathcal{N}\mathcal{N}_\Psi} z^{n-1} \prod_{t=1}^N \left(1 - \frac{z}{x_{(t)}}\right)^{-\tilde{n}_{(t)} + \frac{\epsilon_{(t)}}{2}}$$

Vacua

Define the **vacuum** with respect to b_n :

$$b_n \left| \{x_{(t)}\} \right\rangle = 0 \quad \text{for } n \geq 1$$

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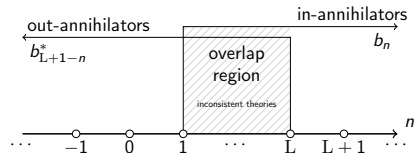
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Theories are subject to consistency conditions:

$$L = n_{(t)} + \tilde{n}_{(t)}$$



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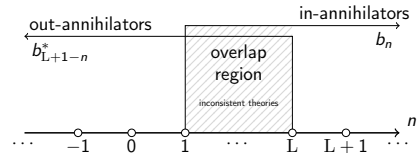
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Stress-energy Tensor and CFT Approach

Compute the OPEs leading to the stress-energy tensor:

$$\mathcal{T}(z) = \frac{\pi T}{2} \mathcal{N}_{\Psi}^2 \sum_{n, m=-\infty}^{+\infty} : b_n b_m^* : z^{-n-m} \left[\frac{m-n}{2} + 2 \sum_{t=1}^N \frac{n_{(t)} + \frac{\epsilon_{(t)}}{2}}{z - x_{(t)}} \right] + \frac{1}{2} \left(\sum_{t=1}^N \frac{n_{(t)} + \frac{\epsilon_{(t)}}{2}}{z - x_{(t)}} \right)^2$$

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Invariant Vacuum and Spin Fields

$$|\{x_{(t)}\}\rangle = \mathcal{N}(\{x_{(t)}\}) \mathcal{R} \left[\prod_{t=1}^M S_{(t)}(x_{(t)}) \right] |0\rangle_{\text{SL}_2(\mathbb{R})}$$

Spin Fields Amplitudes

Equivalence with Bosonization

$$\partial_{x_{(t)}} \langle \{x_{(t)}\} | \{x_{(t)}\} \rangle = \oint_{x_{(t)}} \frac{dz}{2\pi i} \frac{\langle \{x_{(t)}\} | \mathcal{T}(z) | \{x_{(t)}\} \rangle}{\langle \{x_{(t)}\} | \{x_{(t)}\} \rangle}$$

$$\Rightarrow \langle \{x_{(t)}\} | \{x_{(t)}\} \rangle = \mathcal{N}(\{\epsilon_{(t)}\}) \prod_{\substack{t=1 \\ t>u}}^N (x_{(u)} - x_{(t)})^{n_{(u)} + \frac{\epsilon_{(u)}}{2}} (n_{(t)} + \frac{\epsilon_{(t)}}{2})$$

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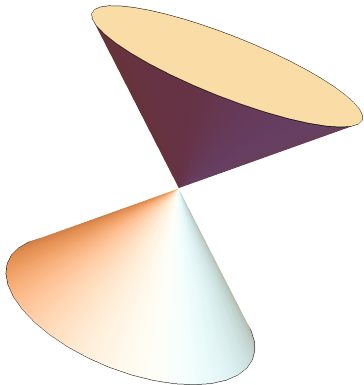
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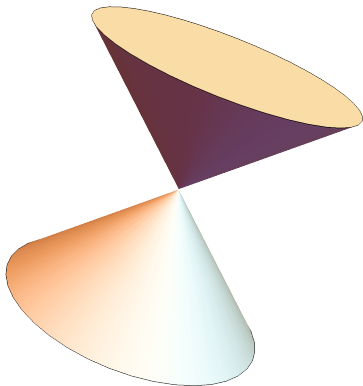


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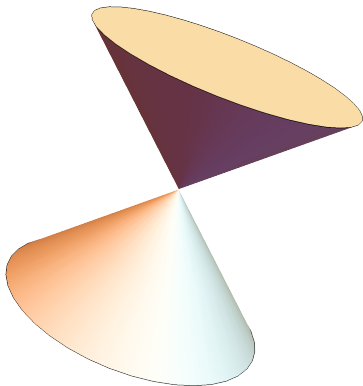


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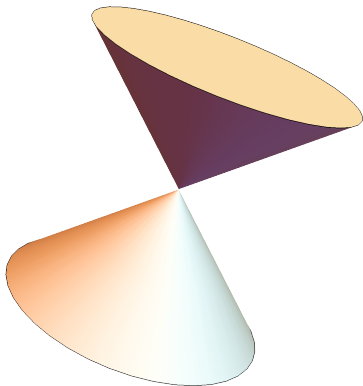


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time-dependent orbifold models

Orbifolds

Mathematics

- manifold M
- (Lie) group G
- stabilizer $G_p = \{g \in G \mid gp = p \in M\}$
- orbit $Gp = \{gp \in M \mid g \in G\}$
- charts $\phi = \pi \circ \mathcal{P}$ where:
 - $\mathcal{P}: U \subset \mathbb{R}^n \rightarrow U/G$
 - $\pi: U/G \rightarrow M$

$\Rightarrow$

Physics

- global orbit space M/G
- G group of isometries
- fixed points
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Use **time-dependent orbifolds** to model **space-like singularities**:

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Divergences

Even in simple models (e.g. NBO, more on this later) the 4 tachyons amplitude is divergent **at tree level**:

$$A_4 \sim \int_{q \sim \infty} \frac{dq}{|q|} \mathcal{A}(q)$$

where

$$\mathcal{A}_{\text{closed}}(q) \sim q^{4-\alpha' \|\vec{p}_\perp\|^2} \quad \text{and} \quad \mathcal{A}_{\text{open}}(q) \sim q^{1-\alpha' \|\vec{p}_\perp\|^2} \text{tr}([T_1, T_2]_+ [T_3, T_4]_+)$$

Null Boost Orbifold

Start from $(x^+, x^-, x^2, \vec{x}) \in \mathcal{M}^{1,D-1}$:

$$\begin{cases} u &= x^- \\ z &= \frac{x^2}{\Delta x^-} \\ v &= x^+ - \frac{1}{2} \frac{(x^2)^2}{x^-} \end{cases} \Rightarrow ds^2 = -2 du dv + (\Delta u)^2 dz^2 + \delta_{ij} dx^i dx^j$$

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$$\kappa = -i(2\pi\Delta)J_{+2} = 2\pi\partial_z \Rightarrow z \sim z + 2\pi n$$

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Consider scalar QED:

$$\Phi_{\{k_+, l, \vec{k}, r\}}(u, v, z, \vec{x}) = e^{i(k_+ v + l z + \vec{k} \cdot \vec{x})} \tilde{\Phi}_{\{k_+, l, \vec{k}, r\}}(u) = \frac{e^{i(k_+ v + l z + \vec{k} \cdot \vec{x})}}{\sqrt{(2\pi)^D |2\Delta k_+|}} e^{-i \frac{l^2}{2\Delta^2 k_+} \frac{1}{u} + i \frac{\|\vec{k}\|^2 + r}{2k_+} u}$$

Scalar QED Interactions

Scalar-photon interactions:

$$S_{\text{sQED}}^{(\text{int})} = \int_{\Omega} d^D x \sqrt{-g} \left(-i e g^{\alpha\beta} a_{\alpha} (\phi^* \partial_{\beta} \phi - \partial_{\beta} \phi^* \phi) + e^2 g^{\alpha\beta} a_{\alpha} a_{\beta} |\phi|^2 - \frac{g^4}{4} |\phi|^4 \right)$$

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Terms involved:

$$\mathcal{I}_{\{N\}}^{[\nu]} = \int_{-\infty}^{+\infty} du |\Delta u| u^{\nu} \prod_{i=1}^N \tilde{\phi}_{\{k_{+(i)}, l_{(i)}, \vec{k}_{(i)}, r_{(i)}\}}(u)$$

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most terms **do not converge** and cannot be recovered even with a **distributional interpretations** due to the term $\propto u^{-1}$ in the exponentatial

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So far:

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Massive String States

$$V_M(x; k, S, \xi) =: \left(\frac{i}{\sqrt{2\alpha'}} \xi \cdot \partial_x^2 X(x, x) + \left(\frac{i}{\sqrt{2\alpha'}} \right)^2 S_{\alpha\beta} \partial_x X^\alpha(x, x) \partial_x X^\beta(x, x) \right) e^{ik \cdot X(x, x)}:$$

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*string theory cannot do **better than field theory** (EFT) if the latter **does not exist** (even a Wilson line around z does not prevent such behaviour)*

Resolution and Motivation

Introduce the generalised NBO:

$$\begin{cases} u &= x^- \\ z &= \frac{1}{2x^-} \left(\frac{x^2}{\Delta_2} + \frac{x^3}{\Delta_3} \right) \\ w &= \frac{1}{2x^-} \left(\frac{x^2}{\Delta_2} - \frac{x^3}{\Delta_3} \right) \\ v &= x^+ - \frac{1}{2x^-} \left((x^2)^2 + (x^3)^2 \right) \end{cases}$$

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Distributional Interpretation

$$\tilde{\Phi}_{\{k_+, p, l, \vec{k}, r\}}(u) = \frac{1}{2\sqrt{(2\pi)^D |\Delta_2 \Delta_3 k_+|}} \frac{1}{|u|} e^{-i \left(\frac{1}{8k_+ u} \left[\frac{(l+p)^2}{\Delta_2^2} + \frac{(l-p)^2}{\Delta_3^2} \right] - \frac{\|\vec{k}\|^2 + r}{2k_+} u \right)}$$

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*spacetime singularities are **hidden into contact terms** and interactions with **massive states**
(the gravitational eikonal deals with massless interactions)*

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The Simplest Calabi–Yau

Focus on Calabi–Yau 3-folds:

$$h^{r,s} = \dim_{\mathbb{C}} H_{\bar{\partial}}^{r,s}(M, \mathbb{C}) \quad \Rightarrow \quad \begin{cases} h^{0,0} & = h^{3,0} = 1 \\ h^{r,0} & = 0 \quad \text{if } r \neq 3 \\ h^{r,s} & = h^{3-r,3-s} \\ h^{1,1}, h^{2,1} \in \mathbb{N} \end{cases}$$

The Simplest Calabi–Yau

Focus on Calabi–Yau 3-folds:

$$h^{r,s} = \dim_{\mathbb{C}} H_{\bar{\partial}}^{r,s}(M, \mathbb{C}) \quad \Rightarrow \quad \begin{cases} h^{0,0} & = h^{3,0} = 1 \\ h^{r,0} & = 0 \quad \text{if } r \neq 3 \\ h^{r,s} & = h^{3-r,3-s} \\ h^{1,1}, h^{2,1} & \in \mathbb{N} \end{cases}$$

Complete Intersection Calabi–Yau Manifolds

Intersection of hypersurfaces in

$$\mathcal{A} = \mathbb{P}^{n_1} \times \cdots \times \mathbb{P}^{n_m}$$

where

$$\mathbb{P}^n: \quad \begin{cases} p_a(Z^0, \dots, Z^n) & = P_{l_1 \dots l_a} Z^{l_1} \dots Z^{l_a} = 0 \\ p_a(\lambda Z^0, \dots, \lambda Z^n) & = \lambda^a p_a(Z^0, \dots, Z^n) \end{cases}$$

Representation of the Output

CICY can be generalised to m projective spaces and k equations. The problem is thus mapped to:

$$\mathcal{R}: \mathbb{Z}^{m \times k} \longrightarrow \mathbb{N}$$

$$\left[\begin{array}{c|ccc} \mathbb{P}^{n_1} & a_1^1 & \dots & a_k^1 \\ \vdots & \vdots & \ddots & \vdots \\ \mathbb{P}^{n_m} & a_1^m & \dots & a_k^m \end{array} \right] \longrightarrow h^{1,1} \text{ or } h^{2,1}$$

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Machine Learning Approach

What is $\mathcal{R}$?

$$\mathcal{R}(M) \longrightarrow \mathcal{R}_n(M; w) \quad \text{s.t.} \quad \lim_{n \rightarrow \infty} f(M; w) = \lim_{n \rightarrow \infty} |\mathcal{R}(M) - \mathcal{R}_n(M; w)| = 0$$

Machine Learning

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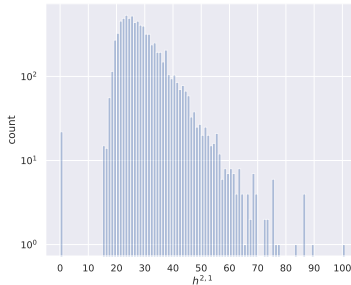
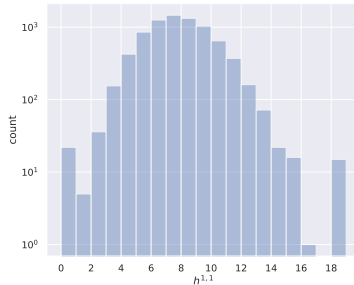
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Exploratory Data Analysis

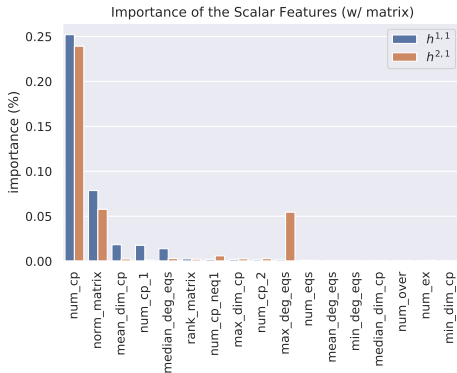
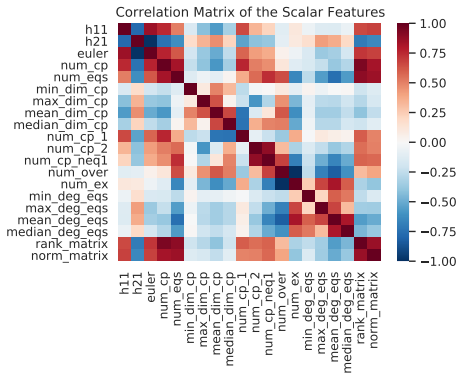
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exploratory data analysis → feature **selection** → Hodge numbers

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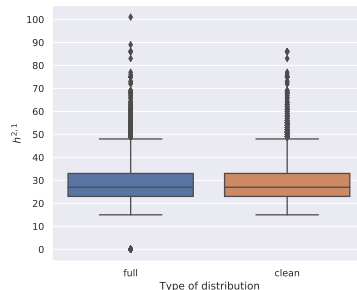
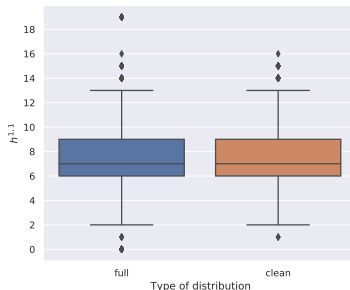
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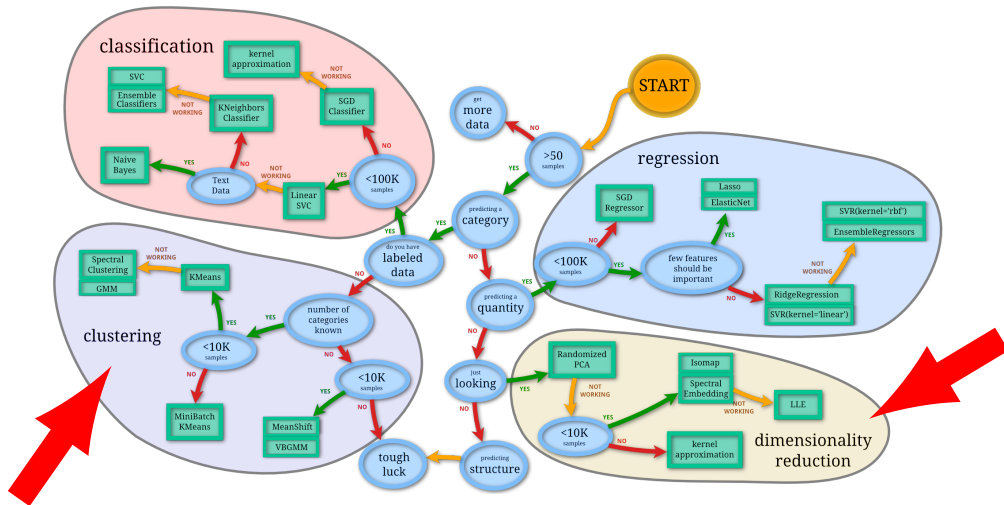
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Machine Learning



The flowchart is organized into four main colored regions:

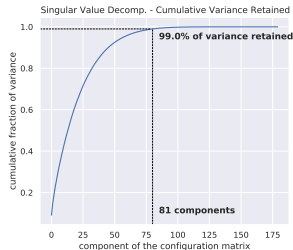
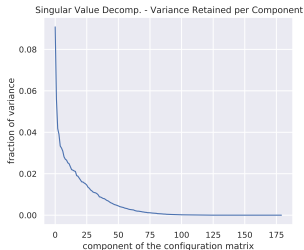
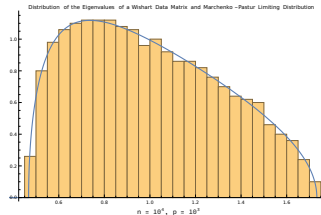
- Classification (Pink):**
 - Starts with 'START' leading to '>50 samples'.
 - If '>50 samples' is YES, it leads to 'predicting a category'.
 - If '>50 samples' is NO, it leads to 'get more data'.
 - 'predicting a category' leads to 'do you have labeled data'.
 - 'do you have labeled data' leads to '<100K samples'.
 - '<100K samples' leads to 'Text Data'.
 - 'Text Data' leads to 'Naive Bayes' (YES) or 'KNeighbors Classifier' (NO).
 - 'KNeighbors Classifier' leads to 'kernel approximation' (YES) or 'SGD Classifier' (NO).
 - 'SGD Classifier' leads to 'SVC Ensemble Classifiers' (YES) or 'Linear SVC' (NO).
 - 'Linear SVC' leads to 'Text Data' (YES) or 'SGD Classifier' (NO).
- Regression (Blue):**
 - Starts with 'START' leading to '>50 samples'.
 - If '>50 samples' is YES, it leads to 'predicting a quantity'.
 - If '>50 samples' is NO, it leads to 'get more data'.
 - 'predicting a quantity' leads to '<100K samples'.
 - '<100K samples' leads to 'new features should be important'.
 - 'new features should be important' leads to 'RidgeRegression SVR(kernel="linear")' (YES) or 'Lasso ElasticNet SVR(kernel="rbf") EnsembleRegressors' (NO).
 - 'RidgeRegression SVR(kernel="linear")' leads to 'SGD Regressor' (YES) or 'Lasso ElasticNet SVR(kernel="rbf") EnsembleRegressors' (NO).
 - 'SGD Regressor' leads to 'Lasso ElasticNet SVR(kernel="rbf") EnsembleRegressors' (YES) or 'RidgeRegression SVR(kernel="linear")' (NO).
- Clustering (Purple):**
 - Starts with 'START' leading to '>50 samples'.
 - If '>50 samples' is YES, it leads to 'predicting a category'.
 - If '>50 samples' is NO, it leads to 'get more data'.
 - 'predicting a category' leads to 'do you have labeled data'.
 - 'do you have labeled data' leads to '<10K samples'.
 - '<10K samples' leads to 'number of categories known'.
 - 'number of categories known' leads to 'KMeans' (YES) or 'MiniBatch KMeans' (NO).
 - 'KMeans' leads to 'Spectral Clustering GMM' (YES) or 'MiniBatch KMeans' (NO).
 - 'MiniBatch KMeans' leads to 'Spectral Clustering GMM' (YES) or 'MeanShift VBGMM' (NO).
 - 'MeanShift VBGMM' leads to 'Spectral Clustering GMM' (YES) or 'tough luck' (NO).
- Dimensionality Reduction (Yellow):**
 - Starts with 'START' leading to '>50 samples'.
 - If '>50 samples' is YES, it leads to 'predicting a quantity'.
 - If '>50 samples' is NO, it leads to 'get more data'.
 - 'predicting a quantity' leads to '<10K samples'.
 - '<10K samples' leads to 'Randomized PCA' (YES) or 'kernel approximation' (NO).
 - 'Randomized PCA' leads to 'Isomap Spectral Embedding' (YES) or 'kernel approximation' (NO).
 - 'Isomap Spectral Embedding' leads to 'LLE' (YES) or 'kernel approximation' (NO).
 - 'kernel approximation' leads to 'LLE' (YES) or 'tough luck' (NO).

Red arrows point to the 'clustering' and 'dimensionality reduction' sections, and a red circle highlights the 'regression' section.

A Word on PCA

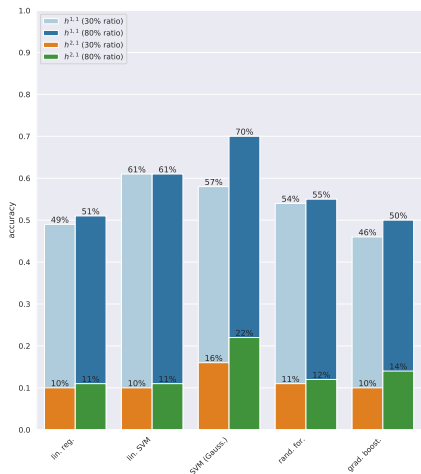
What is PCA for a $X \in \mathbb{R}^{n \times p}$?

- find new coordinates to “**put the variance in order**”
- equivalently compute the **eigenvectors** of XX^T or the **singular values** of X
- isolate **the signal** from the **background**
- ease the machine learning job of finding a better representation of the input



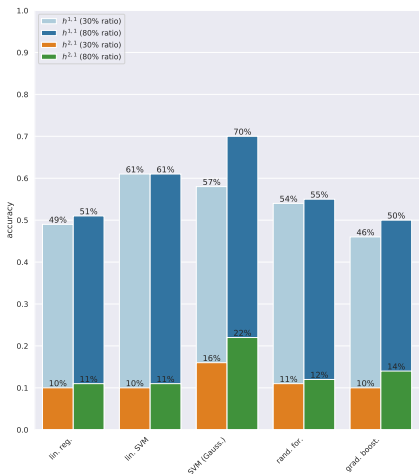
Machine Learning Results

Configuration Matrix Only

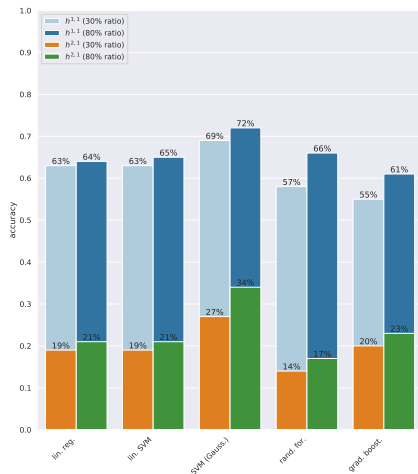


Machine Learning Results

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Best Training Set



Artificial Intelligence and Neural Networks

- use **gradient descent** to optimise **weights**
- learn highly **non linear** representations of the input
- can be “large” to have enough parameters
- can be “deep” to learn **complicated functions**

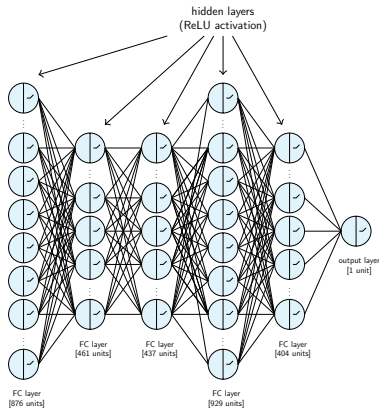
Neural Networks

fully connected: $a^{(i)\{l+1\}} = \phi(a^{(i)\{l\}} \cdot W^{\{l\}} + b^{\{l\}} \mathbf{1})$

convolutional: $a^{(i)\{l+1\}} = \phi(a^{(i)\{l\}} * W^{\{l\}} + b^{\{l\}} \mathbf{1})$

Non linearity ensured by:

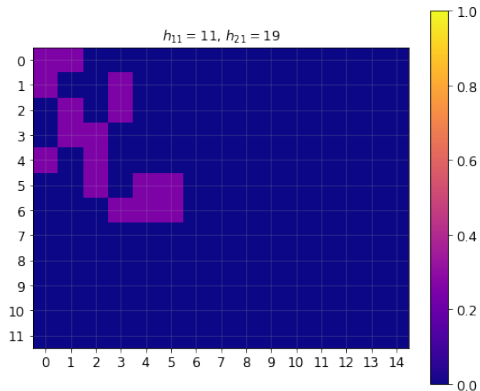
$$\phi(z) = \text{ReLU}(z) = \max(0, z)$$



Convolutional Neural Networks

Why convolutional?

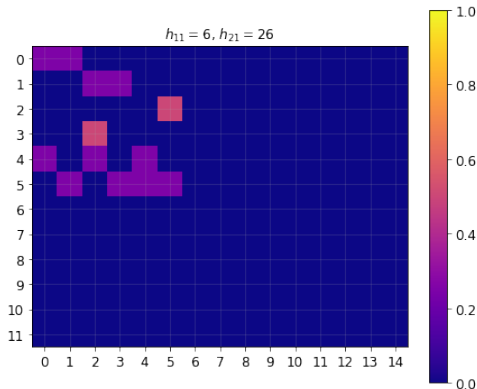
- retain **spacial awareness**



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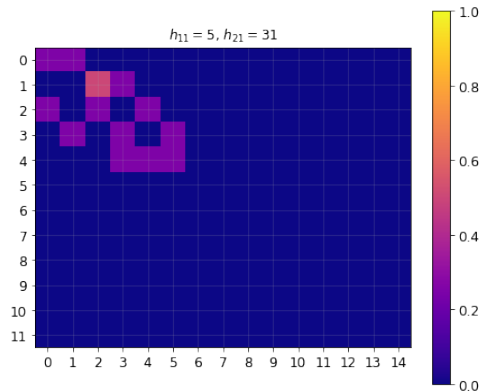
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- smaller **no. of parameters**
($\approx 2 \times 10^5$ vs. $\approx 2 \times 10^6$)



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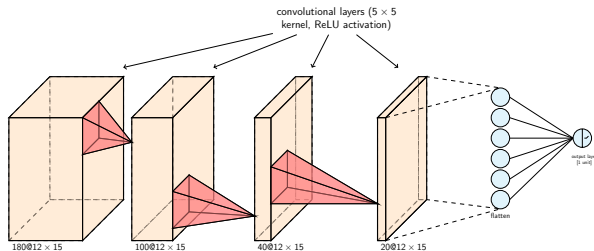
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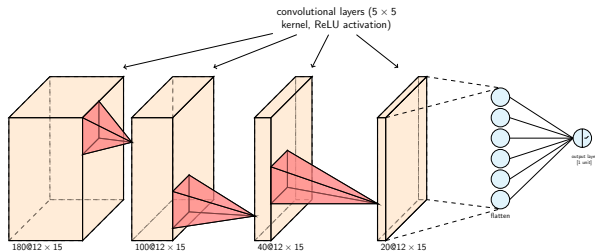
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- CNN can isolate “**defining features**”
- find patterns as in **computer vision**



Inception Neural Networks

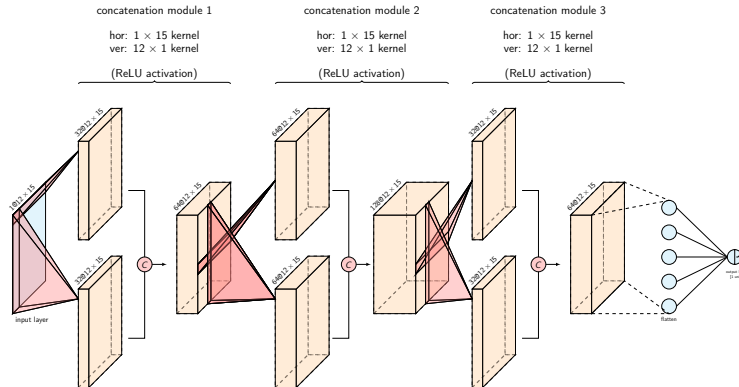
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- neural networks with **better generalisation properties**
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- different **concurrent kernels** (e.g. one over **equations** one over **coordinates**)

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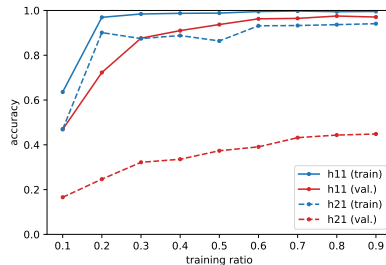
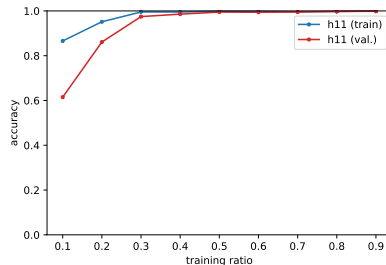
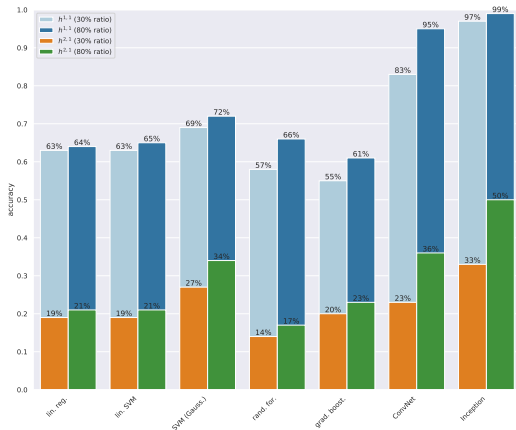
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Deep Learning Results and Generalisation Properties

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A Few Comments and Future Directions

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The End?



THANK YOU!