

# Flowing to the Bounce

So Chigusa

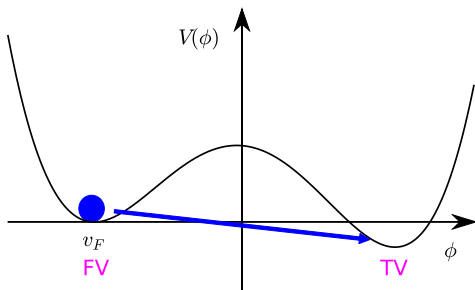
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# Vacuum Decay

Scalar potential with more than one local minima



Tunneling effect allows false vacuum decaying into true vacuum

## Example

SM : Due to the RGE effect,  $\lambda < 0$  for  $Q > 10^{10}$  GeV

MSSM : When scalar tri-linear coupling huge ( $A \gtrsim \sqrt{6}M_{\text{SU5Y}}$ )

2HDM, etc...

# Calculation of decay rate

## Master Formula

$$\gamma = Ae^{-S[\bar{\phi}]}$$

$S[\phi]$  is action,  $A$  is pre-factor

S. R. Coleman (1977), C. G. Callan<sup>+</sup> (1977)

## Bounce configuration $\bar{\phi}$

– Solution of EoM

$$\left. \frac{\delta S[\phi]}{\delta \phi} \right|_{\phi \rightarrow \bar{\phi}} = -\partial_r^2 \bar{\phi} - \frac{D-1}{r} \partial_r \bar{\phi} + \left. \frac{\partial V}{\partial \phi} \right|_{\phi \rightarrow \bar{\phi}} = 0$$

– Boundary conditions

$$\partial_r \bar{\phi}(r=0) = 0, \quad \bar{\phi}(r \rightarrow \infty) = v_F$$

– Spherically symmetric

S. R. Coleman<sup>+</sup> (1978), K. Blum<sup>+</sup> (2017)

# Calculation of decay rate

Bounce should be calculated precisely

- LO contribution to  $\gamma$
- $r \rightarrow \infty$  behavior of bounce is used for evaluation of  $A$
- Numerical calculation is required for more complex models

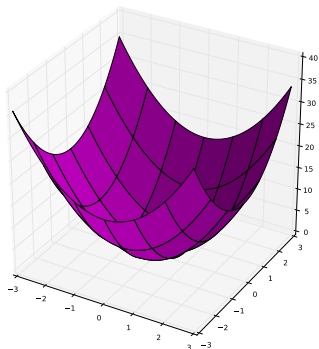
(cf) Calculation of  $A$  is a hard work ... **Example:** SM

G. Isidori<sup>+</sup>(2001), G.Degrassi<sup>+</sup>(2012), A. Andreassen<sup>+</sup>(2017), S. Chigusa<sup>+</sup>(2017, 18)

$$\log_{10} \gamma_{\text{SM}} \times \text{Gyr Gpc}^3 = -582_{-397}^{+237}$$

## Steepest descent for local minimum search

**Example:** Local minimum of multi-scalar potential



$s \dots$  “flow time”

Local minimum search by rolling down the slope

$$\partial_s \Phi_A(s) = - \left. \frac{\partial V}{\partial \phi_A} \right|_{\phi \rightarrow \Phi(s)}$$

Same idea can be applied to local minimum search of functional;

$$\partial_s \Phi_A(s, x) = - \left. \frac{\delta S[\phi_1(x), \phi_2(x), \dots]}{\delta \phi_A(x)} \right|_{\phi(x) \rightarrow \Phi(s, x)}$$

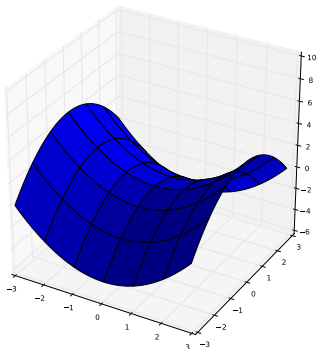
Similar to gradient flow!

# Numerical calculation of bounce in multi-scalar models

Local minimum is a stable fixed point of the flow equation



Bounce configuration is a saddle-point of action



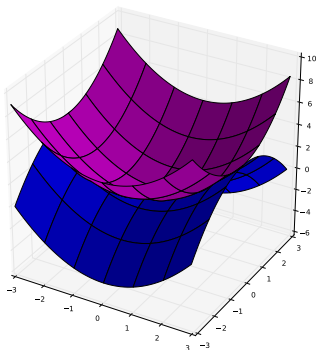
unstable fixed point

# Numerical calculation of bounce in multi-scalar models

Local minimum is a stable fixed point of the flow equation



Bounce configuration is a saddle-point of action



Modification of “gradient”  
may stabilize the bounce!



unstable fixed point

## Action around the bounce

Fluctuation operator around the bounce

$$\mathcal{M}_{AB} \equiv \frac{\delta^2 S}{\delta\phi_A \delta\phi_B} \Big|_{\phi \rightarrow \bar{\phi}} = - \left( \partial_r^2 + \frac{D-1}{r} \partial_r \right) \delta_{AB} + \frac{\partial^2 V}{\partial\phi_A \partial\phi_B} \Big|_{\phi \rightarrow \bar{\phi}}$$

Eigenfunctions  $\chi_{n,A}(r)$  ( $n = -1, 1, 2, \dots$ )

$$\mathcal{M}_{AB} \chi_{n,B} = \lambda_n \chi_{n,A} \quad \text{w/} \quad \begin{cases} \lambda_n < 0 & (n = -1) \\ \lambda_n > 0 & (n \geq 1) \end{cases}$$

$$\partial_r \chi_{n,A}(r=0) = 0 \quad ; \quad \chi_{n,A}(r \rightarrow \infty) = 0$$

Ortho-normality of eigenfunctions

$$\langle \chi_n | \chi_m \rangle = \delta_{n,m}$$

$$\langle f | f' \rangle \equiv \int_0^\infty dr r^{D-1} f_A(r) f'_A(r)$$



## Modified flow equation for bounce

Flow equation

$$\partial_s \Phi_A(r, s) = F_A(r, s) - \beta \langle F | g \rangle g_A(r, s)$$

$$F_A \equiv -\frac{\delta S[\Phi]}{\delta \Phi_A}$$

–  $\beta \neq 1$  controls size of modification

$\beta = 0$  corresponds to the usual steepest descent

–  $g_A(r, s)$  is a normalized function with suitable BCs

$$g_A(r, s) = \sum_{n=-1,1,2,\dots} c_n(s) \chi_{n,A}(r) \quad ; \quad \langle g | g \rangle = \sum_n c_n^2 = 1$$

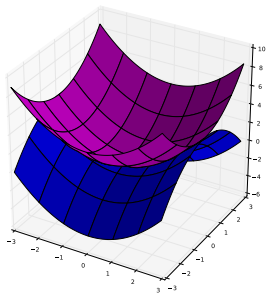
– Fixed points ( $\partial_s \Phi_A = 0$ ) = solutions of EoM ( $F_A = 0$ )

**proof**

$$\langle \partial_s \Phi | g \rangle = (1 - \beta) \langle F | g \rangle = 0$$

$$\partial_s \Phi_A = F_A - \beta \langle F | g \rangle g_A = 0$$

# Stability?



Expansion around bounce

$$\Phi_A(r, s) = \bar{\phi}_A(r) + \sum_n a_n(s) \chi_{n,A}$$

Linearized flow equation

$$\dot{a}_n \simeq -\lambda_n a_n + \beta \sum_m c_n c_m \lambda_m a_m + \mathcal{O}(a_n^2)$$

## Asymptotic behavior of linearized equation

Linearized flow equation

$$\dot{a}_n \simeq -\lambda_n a_n + \beta \sum_m c_n c_m \lambda_m a_m \equiv - \sum_m \Gamma_{nm}(\beta) a_m$$

Condition for stability of bounce =  $a_n \rightarrow 0$  at  $s \rightarrow \infty$

Let  $\{\gamma_\alpha\}$  be the set of eigenvalues of  $\Gamma$

Iff  $\text{Re } \gamma_\alpha > 0$  for  $\forall \alpha$ ,  $a_n \rightarrow 0$

(cf) Case with  $\beta = 0$

- $\Gamma(\beta = 0) = \text{diag}(\lambda_{-1}, \lambda_1, \dots)$
- $\{\gamma_\alpha\} = \{\lambda_n\}$
- Existence of  $\lambda_{-1} < 0$  destabilizes the bounce

## Suitable choice of $\beta$ and $g_A$

One of necessary conditions

$$\det \Gamma = (1 - \beta) \prod_n \lambda_n > 0$$

- $\beta > 1$  is suitable for bounce search (with  $\lambda_{-1} < 0$ )
- For  $\beta > 1$ , all FV configurations are destabilized

It also helps fast convergence (though not necessary)

$$\langle g | \mathcal{M}g \rangle = \sum_n \lambda_n c_n^2 < 0$$

$$\frac{1}{c_{-1}^2} < \beta < \frac{1}{\max_{n \geq 1} c_n^2}$$

Guideline for modification

$g_A$  should contain large fraction of  $\chi_{-1,A}$

$$c_{-1}^2 \gg c_{n \geq 1}^2$$

## Example of $g_A$

A good choice of  $g_A$  we used

$$g_A(r, s) \propto r \partial_r \Phi(r, s)$$

- Direction of scaling transf., along which  $\delta^2 S / \delta \phi^2 < 0$
- Behavior of  $g_A$  around bounce

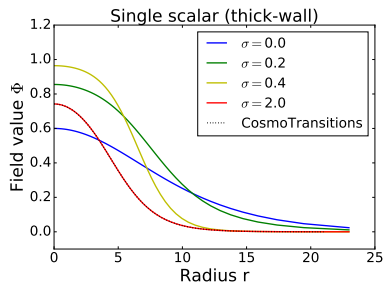
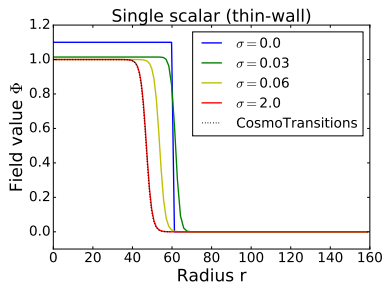
$$\langle g | \mathcal{M}g \rangle |_{\Phi \rightarrow \bar{\phi}} < 0 \quad (D > 2)$$

### Flowing to the Bounce

For  $D > 2$ ,  $\beta \gtrsim 1$ , and  $g_A(r, s) \propto r \partial_r \Phi(r, s)$ , **stable fixed points are always identified as non-trivial solutions of the EoM such as the bounce**

## Numerical results I: single scalar model

$$V(\phi) = \frac{1}{4}\phi^4 + \frac{c_1 + 1}{3}\phi^3 + \frac{c_1}{2}\phi^2$$



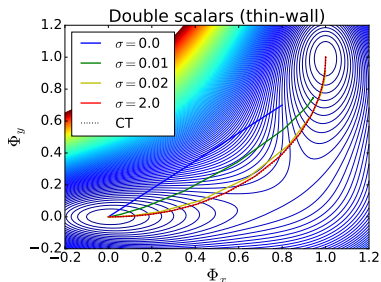
Thin-wall:  $c_1 = 0.47$

Thick-wall:  $c_1 = 0.2$

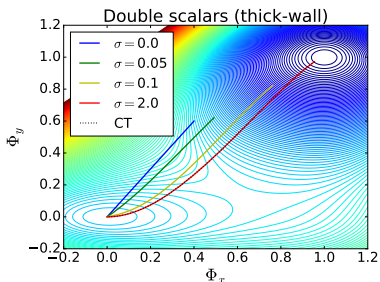
- Results agrees well with **CosmoTransitions** [C. L. Wainwright \(2012\)](#)
- $r \rightarrow \infty$  behavior can be better understood in our method

## Numerical results II: multi-scalar model

$$V(\phi) = (\phi_x^2 + 5\phi_y^2) \left[ 5(\phi_x - 1)^2 + (\phi_y - 1)^2 \right] + c_2 \left( \frac{1}{4}\phi_y^4 - \frac{1}{3}\phi_y^3 \right)$$



Thin-wall:  $c_2 = 2$



Thick-wall:  $c_2 = 80$

## Numerical results III: comparison of bounce action

Table of  $S[\bar{\phi}]$  for each model

Model	Our method	CosmoTransitions
Single scalar thin-wall	1086.6	1092.8
Single scalar thick-wall	6.6360	6.6490
Multi-scalar thin-wall	1763.7	1767.7
Multi-scalar thick-wall	4.4585	4.4661

– Consistent decay rate can be derived



# Conclusion

We proposed a new way of calculating multi-field bounce configuration using steepest descent method.

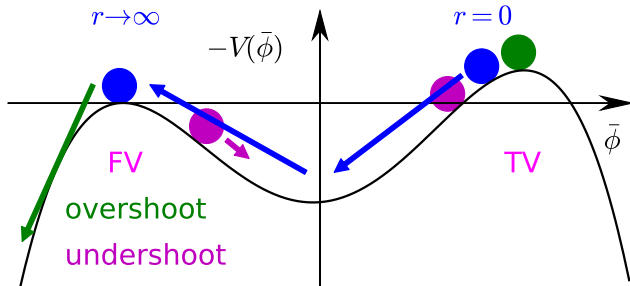
- Applicable to general multi-scalar potential
- Better way to understand  $r \rightarrow \infty$  behavior of bounce compared with other existing methods
- Applicable to the search of saddle points in general

Backup slides

## Single scalar model ( Example : SM )

$$\underbrace{\partial_r^2 \bar{\phi}}_{\text{acceleration}} + \underbrace{\frac{D-1}{r} \partial_r \bar{\phi}}_{\text{friction term}} = \underbrace{\frac{\partial V}{\partial \phi} \Big|_{\phi \rightarrow \bar{\phi}}}_{\text{potential } -V[\bar{\phi}]}$$

EoM for an object moving under the potential  $-V[\bar{\phi}]$



This method cannot be applied for multi-scalar case

## Fixed point of flow

Flow equation

$$\partial_s \Phi_A(r, s) = F_A(r, s) - \beta \langle F | g \rangle g_A(r, s)$$

$$\langle \partial_s \Phi | g \rangle = (1 - \beta) \langle F | g \rangle \quad \dots (*)$$

$\Phi(r, s \rightarrow \infty)$  is a solution of EoM ( $F_A = 0$ ) for  $\beta \neq 1$

**Proof:**

1. Fixed point satisfies  $\partial_s \Phi_A = 0$
2.  $F_A = 0$  or  $F_A$  should be parallel to  $g_A$  ( $\langle F | g \rangle \neq 0$ )
3. (\*) confirms  $F_A = 0$

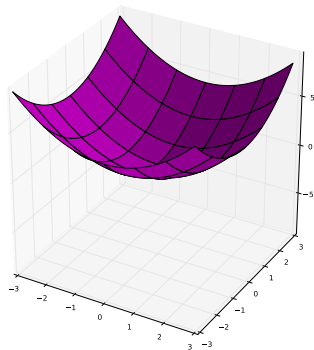
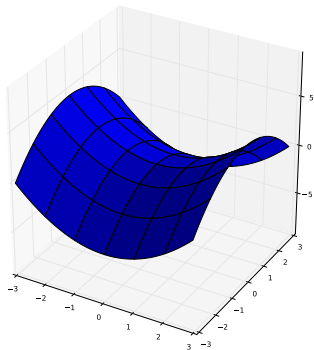
## Asymptotic behavior of linearized equation

Linearized flow equation

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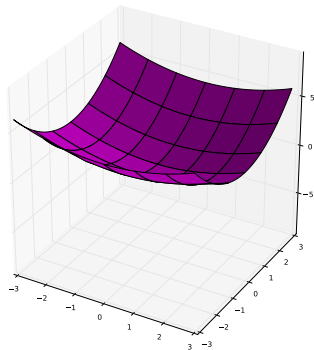
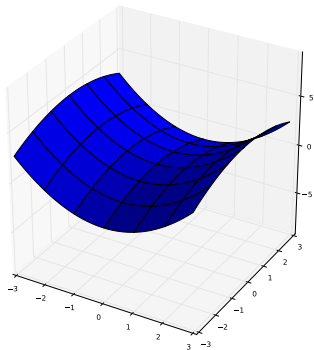
# Illustration of our method

(bounce)  $\beta = 0$  (FV)



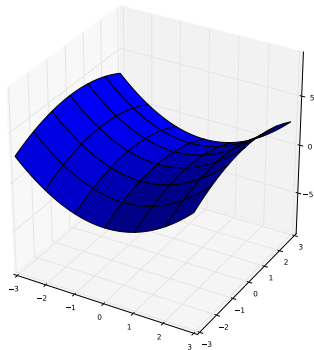
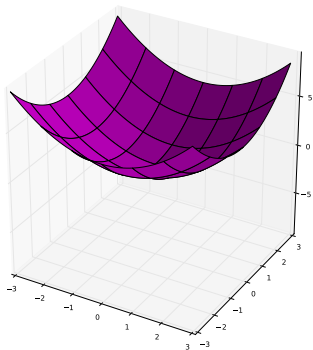
# Illustration of our method

(bounce)  $0 < \beta < 1$  (FV)



# Illustration of our method

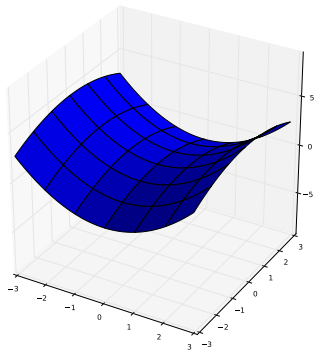
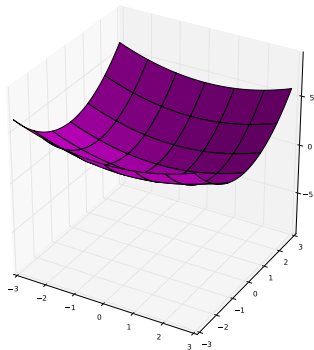
(bounce)  $\beta \gtrsim 1$  (FV)





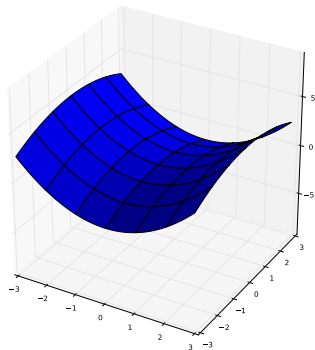
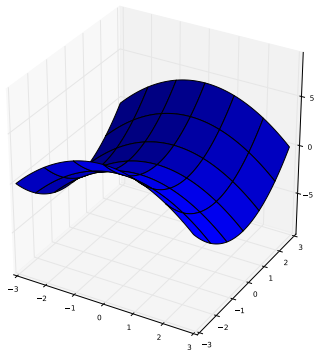
# Illustration of our method

(bounce)  $\beta \gtrsim 1$  (FV)



# Illustration of our method

(bounce)  $\beta \gg 1$  (FV)



Requires  $\beta_{\text{stabilization}} < \beta < \beta_{\text{destabilization}}$

## memo

- Dilatation maximization : After minimize the kinetic energy  $T$  for some  $V < 0$ , perform the dilatation transformation and maximize the action.
- Improved action : Use  $T + 2V$  to modify the action without changing the position of bounce. However, the bounce position is just a local minimum and we should carefully choose the BC.
- Squared EoM : Minimize the  $(\text{EoM})^2$  which should become zero if the configuration is a solution of EoM.
- Back step : Combine small steepest descents and a large steepest 'assent'. Tendency to converge both local minimum and maximum (including saddle points).
- Improved potential :
- Path deformation : Devide the "gradient force" into the path direction and path deformation (perpendicular to path) direcction. On a path, the EoM is just the same as the overshoot and undershoot problem.
- Perturbative method : Semi-analytic calculation using some ansatz plus perturbation.
- Multiple shooting : Improved version of overshoot / undershoot for multifield case.
- Tunneling potential : A short cut to evaluate bounce action using modified potential.
- Polygon approximation : Approximate the potential with combination of several patches of linear potential. Then we can derive some analytital expression to approximate the bounce configuration.
- Machine learning : Use image recognition.