# The dPG Paradigm <br> —discontinuous Petrov-Galerkin 4 CENTRAL— 

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## Outline

- dPG Framework
- minimal residual method
- mixed problem
- a posteriori error analysis
- Applications
- Poisson model problem
- Stokes equations
- linear elasticity
- Maxwell equations
- Adaptive dPG
- adaptive least-squares FEM


## The dPG Methodology

+ instant stability
+ built-in error control
+ general geometries
+ flexible modelling
+ parallel computing
- more degrees of freedom

References. Demkowicz, Gopalakrishnan (since 2010)
[CDG14], [CDG16], and recent publications

## dPG Framework

" dPG is a minimal residual method with piecewise discontinuous test functions"

## Minimal Residual Method

Suppose $b: X \times Y \rightarrow \mathbb{R}$ is a bdd bilinear form on real Hilbert spaces $X$ and $Y$ with inf-sup condition

Continuous problem (P) with given RHS $F \in Y^{*}$ seeks

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u \in X \quad \text { with } \quad b(u, \bullet)=F \text { in } Y
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Suppose (exclusively on the continuous level), in addition, non-degeneracy in that

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\forall y \in Y \backslash\{0\} \quad b(\bullet, y) \not \equiv 0
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Suppose (exclusively on the continuous level), in addition, non-degeneracy in that

$$
\forall y \in Y \backslash\{0\} \quad b(\bullet, y) \not \equiv 0
$$

so that $(P)$ has a unique solution. The minimal residual method considers

$$
u \in \underset{x \in X}{\arg \min }\|b(x, \bullet)-F\|_{Y *} .
$$

This is sensitive without any further condition on $b$ bdd bilinear with $\beta>0$.

## Discretization in Minimal Residual Method

Let $X_{h} \subset X$ and $Y_{h} \subset Y$ be closed (e.g. finite-dimensional) subspaces with

$$
0<\beta_{h}:=\inf _{\substack{x_{h} \in X_{h} \\\left\|x_{h}\right\|_{x}=1}} \sup _{\substack{y_{h} \in Y_{h} \\\left\|y_{h}\right\|_{Y}=1}} b\left(x_{h}, y_{h}\right)
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Petrov-Galerkin discretization requires a non-degeneracy condition on the discrete level and leads to $\operatorname{dim} X_{h}=\operatorname{dim} Y_{h} \in \mathbb{N}_{0} \cup\{\infty\}$.

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$$

Petrov-Galerkin discretization requires a non-degeneracy condition on the discrete level and leads to $\operatorname{dim} X_{h}=\operatorname{dim} Y_{h} \in \mathbb{N}_{0} \cup\{\infty\}$. In what follows, $\operatorname{dim} X_{h}<\operatorname{dim} Y_{h}$ and this is not a Petrov-Galerkin discretization but suits for a minimal residual method

$$
\left(\min ^{\left.\operatorname{Res}_{h}\right)} \quad u_{h} \in \underset{x_{h} \in X_{h}}{\arg \min }\left\|b\left(x_{h}, \bullet\right)-F\right\|_{Y_{h}^{*}}\right.
$$

Alternative formulation: Seek $\left(u_{h}, v_{h}\right) \in X_{h} \times Y_{h}$ with
$\left(\mathrm{M}_{h}\right) \quad\left\{\begin{aligned} b\left(x_{h}, v_{h}\right) & =0 & & \text { for all } x_{h} \in X_{h} \\ \left(v_{h}, y_{h}\right)_{Y}+b\left(u_{h}, y_{h}\right) & =F\left(y_{h}\right) & & \text { for all } y_{h} \in Y_{h}\end{aligned}\right.$

## Theorem. $\quad\left(\right.$ minRes $\left._{h}\right) \Longleftrightarrow\left(\mathrm{M}_{h}\right)$

Proof. $R_{Y_{h}}: Y_{h} \rightarrow Y_{h}^{*}, y_{h} \mapsto\left(y_{h}, \bullet\right)_{Y}$ Riesz map
" $\Longrightarrow " u_{h} \in X_{h}$ solves ( $\operatorname{minRes}_{h}$ ) implies for all $t \in \mathbb{R}, x_{h} \in X_{h}$

$$
\begin{aligned}
\left\|F-b\left(u_{h}, \bullet\right)\right\|_{Y_{h}^{*}}^{2} & \leqslant\left\|F-b\left(u_{h}+t x_{h}, \bullet\right)\right\|_{Y_{h}^{*}}^{2} \\
& =\| \underbrace{\| R_{Y_{h}}^{-1}\left(F-b\left(u_{h}, \bullet\right)\right)}_{=: v_{h} \Longleftrightarrow}-t R_{Y_{h}}^{-1} b\left(v_{h}, \bullet \bullet\right)_{Y}+b\left(u_{h}, \bullet\right)=F \text { in } Y_{h} \\
& =\underbrace{\left\|v_{h}\right\|_{Y}^{2}}_{=\left\|F-b\left(u_{h}, \bullet\right)\right\|_{Y_{h}}^{2}}-2 t b\left(x_{h}, v_{h}\right)+t^{2}\left\|b\left(x_{h}, \bullet\right)\right\|_{Y_{h}^{*}}^{2}
\end{aligned}
$$

Hence $b\left(\bullet, v_{h}\right)=0$ in $X_{h}$

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& =\underbrace{\left\|v_{h}\right\|_{Y}^{2}-2 t b\left(x_{h}, v_{h}\right)+t^{2}\left\|b\left(x_{h}, \bullet\right)\right\|_{Y_{h}^{*}}^{2}}_{=\left\|F-b\left(u_{h}, \bullet\right)\right\|_{Y_{h}^{*}}^{2}}
\end{aligned}
$$

Hence $b\left(\bullet, v_{h}\right)=0$ in $X_{h}$
$" \Longleftarrow "\left(u_{h}, v_{h}\right) \in X_{h} \times Y_{h}$ solves $\left(\mathrm{M}_{h}\right)$ implies

$$
\left\|F-b\left(u_{h}+t x_{h}, \bullet\right)\right\|_{Y_{h}^{*}}^{2}=\left\|v_{h}\right\|_{Y}^{2}-2 t \underbrace{b\left(x_{h}, v_{h}\right)}_{=0}+t^{2}\left\|b\left(x_{h}, \bullet\right)\right\|_{Y_{h}^{*}}^{2}
$$

## dPG as Mixed Problem

Brezzi splitting lemma. $\left(M_{h}\right)$ is well-posed iff

$$
0<\beta_{h}:=\inf _{\substack{x_{h} \in X_{h} \\\left\|x_{h}\right\| X_{x}=1}} \sup _{\substack{y_{h} \in Y_{h} \\\left\|y_{h}\right\|_{Y}=1}} b\left(x_{h}, y_{h}\right)
$$

Fortin criterion: $\beta_{h}>0$ is equivalent to the existence of a projection $P: Y \rightarrow Y$ (i.e. linear, bdd, idempotent) onto $Y_{h}=P(Y)$ with annulation property

$$
b(\bullet, y-P y)=0 \quad \text { in } X_{h}
$$

[cf. e.g. FE-book by D.Braess]
Then

$$
0<\beta /\|P\| \leqslant \beta_{h}
$$

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Then

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$$

General theory of mixed formulations leads to $\gamma_{h}=\gamma_{h}\left(\|b\|, 1, \beta_{h}\right)$ : Solution $u \in X$ to $b(u, \bullet)=F$ and $v=0$ satisfy best-approximation property in the ansatz space only

$$
\left\|u-u_{h}\right\|_{X}^{2}+\left\|0-v_{h}\right\|_{Y}^{2} \leqslant\|b\| \gamma_{h}^{-1} \min _{x_{h} \in X_{h}}\left\|u-x_{h}\right\|_{X}^{2}
$$

## Proof of Fortin Criterion " $\Rightarrow$ "

Since $\beta_{h}>0$, the discrete mixed problem has a unique solution for all right-hand sides. Given any $y \in \mathrm{Y}$, consider the right-hand side $(F, G):=\left((y, \cdot)_{\mathrm{Y}_{h}},\left.b(\cdot, y)\right|_{\mathrm{x}_{h}}\right) \in \mathrm{Y}_{h}^{*} \times \mathrm{X}_{h}^{*}$ and the unique solution $\left(v_{h}, u_{h}\right) \in \mathrm{Y}_{h} \times \mathrm{X}_{h}$ to (a) $\left(v_{h}, \cdot\right)_{\mathrm{Y}}+b\left(u_{h}, \cdot\right)=(y, \cdot)_{\mathrm{Y}}$ in $\mathrm{Y}_{h}$.
(b) $b\left(\cdot, v_{h}\right)=b(\cdot, y)$ in $\mathrm{X}_{h}$.

The map $y \mapsto\left(v_{h}, u_{h}\right)$ is linear and so $v_{h}=$ : Py defines $P \in L(\mathrm{Y}, \mathrm{Y})$. If $y \in \mathrm{Y}_{h}$, then $(y, 0)$ solves (a)-(b). Uniqueness of discrete solutions proves $y=P y$. That is $P=P^{2}$. The annullation property is (b).

## Proof of Fortin Criterion " $\Leftarrow "$

Given $x_{h} \in S\left(\mathrm{X}_{h}\right) \subset S(\mathrm{X})$, the inf-sup condition of $\beta>0$ leads to $y \in S(\mathrm{Y})$ in the Hilbert space Y with

$$
\begin{aligned}
\beta & \leqslant\left\|b\left(x_{h}, \cdot\right)\right\|_{\mathrm{Y}^{*}}=b\left(x_{h}, y\right) \stackrel{!}{=} b\left(x_{h}, P y\right) \\
& \leqslant\left\|b\left(x_{h}, \cdot\right)\right\|_{\mathrm{Y}_{h}^{*}}^{* P y \underbrace{\|P\|_{\mathrm{Y}_{h}}}_{\leqslant\|P\|}} .
\end{aligned}
$$

Hence $\beta /\|P\| \leqslant\left\|b\left(x_{h}, \cdot\right)\right\|_{\mathrm{Y}_{h}^{*}}$. Since $x_{h} \in S\left(\mathrm{X}_{h}\right)$ is arbitrary, this proves

$$
0<\beta /\|P\| \leqslant \beta_{h}:=\inf _{x_{h} \in S\left(\mathrm{X}_{h}\right)} \overbrace{\sup _{y_{h} \in S\left(\mathrm{Y}_{h}\right)} b\left(x_{h}, y_{h}\right)}^{\left\|b\left(x_{h}, \cdot\right)\right\|_{\mathrm{Y}_{h}^{*}}} \square
$$

(R1) $P$ is an oblique projection (not an orthogonal projection in general) and Kato lemma asserts $\|P\|=\|1-P\|$ (provided $P \neq 0,1$ ). (R2) The theorem holds in general Banach spaces as pointed out in [ Ern, A. and Guermond, J.-L., A converse to Fortin's Lemma in Banach spaces, Comptes Rendus de l'Academie des sciences Serie I,2016.]

## A Posteriori Error Analysis

Suppose $b(u, \bullet)=F$ is well-posed (i.e. $\beta>0$ and non-degeneracy condition) on the continuous level. The bilinear form leads to the operator $B_{1}: X \rightarrow Y^{*}, x \mapsto b(x, \bullet)$ and its dual $B_{2}: Y \rightarrow X^{*}, y \mapsto b(\bullet, y)$. Well-posedness means that $B_{1}$ and $B_{2}$ are invertible and and the inverse is bounded by $1 / \beta$. Those mapping properties lead to equivalence

$$
\left\|u-u_{h}\right\|_{X}^{2}+\left\|v_{h}\right\|_{Y}^{2} \approx\left\|b\left(\bullet, v_{h}\right)\right\|_{X^{*}}^{2}+\left\|F-b\left(u_{h}, \bullet\right)+\left(v_{h}, \bullet\right)_{Y}\right\|_{Y^{*}}^{2}
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$$

Since $B_{2}$ is invertible and bdd,

$$
\beta\left\|v_{h}\right\|_{Y} \leqslant\left\|b\left(\bullet, v_{h}\right)\right\|_{X *} \leqslant\|b\|\left\|v_{h}\right\|_{Y}
$$

and $\left\|v_{h}\right\|_{Y}$ is the computable norm of the residual.

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For all $y \in Y$ with norm 1, the annulation operator $P: Y \rightarrow Y$ with range $P(Y)=Y_{h}$ and the discrete equations in $\left(M_{h}\right)$ lead to

$$
F(y)-b\left(u_{h}, y\right)+\left(v_{h}, y\right)_{Y}=F(y-P y)-b\left(u_{h}, y-P y\right)+\left(v_{h}, y-P y\right)_{Y}
$$

Since $b\left(u_{h}, y-P y\right)=0$ and $\left|\left(v_{h}, y-P y\right)_{Y}\right| \leqslant\left\|v_{h}\right\|_{Y}\|P\|$, it follows

$$
\left\|u-u_{h}\right\|_{X}^{2}+\left\|v_{h}\right\|_{Y}^{2} \approx \underbrace{\left\|v_{h}\right\|_{Y}^{2}}_{\text {comnutahle }}+\underbrace{\|F \circ(1-P)\|_{Y^{*}}^{2}}_{\text {hichor order? }}
$$

## 1. Extreme Example in PMP Shows LS $\subset \mathrm{dPG}$

The Poisson model problem (PMP) seeks $u \in H_{0}^{1}(\Omega)$ with $-\Delta u=f$ in $\Omega$ in the weak sense for a given RHS $f \in L^{2}(\Omega)$.

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p \in H(\operatorname{div}, \Omega) \text { and } u \in H_{0}^{1}(\Omega) \text { with } \quad p=\nabla u \quad \text { and } \quad f+\operatorname{div} p=0
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$$

For all $(q, v) \in X=H(\operatorname{div}, \Omega) \times H_{0}^{1}(\Omega)$ define

$$
B_{1}(q, v):=(q-\nabla v, \operatorname{div} q) \in Y=L^{2}\left(\Omega ; \mathbb{R}^{n}\right) \times L^{2}(\Omega)
$$

The PMP is equivalent to $B_{1}(p, u)=(0,-f)$. Since $Y \equiv Y^{*}$, any $(q, v) \in X$ allows for

$$
\|b(q, v ; \bullet)\|_{Y^{*}}=\sqrt{\|q-\nabla v\|^{2}+\|\operatorname{div} q\|^{2}}
$$

The theory of least-squares FEM (LS) shows that this is indeed equivalent to $\|(q, v)\|_{X}$ and, in fact, this dPG method is a LS. This also shows that any discretisation $X_{h} \subset X$ is stable and quasi-optimal.

## 2. Extreme Example in PMP is Infeasible

 In continuation of the PMP, define for any $(q, v) \in X=L^{2}\left(\Omega ; \mathbb{R}^{n}\right) \times H_{0}^{1}(\Omega)$$$
B_{1}(q, v):=(q-\nabla v, \operatorname{div} q) \in Y=L^{2}\left(\Omega ; \mathbb{R}^{n}\right) \times H^{-1}(\Omega) .
$$

This leads to a LS with discrete problem (which is always stable)

$$
\min _{(q, v) \in X}\left(\|q-\nabla v\|^{2}+\|f+\operatorname{div} q\|_{H^{-1}(\Omega)}^{2}\right)
$$

The computation of $\|f+\operatorname{div} q\|_{H^{-1}(\Omega)}$ requires an approximation of the dual norm. The BPX precondition has been suggested to allow a practical variant and is an established LS.

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$$

The computation of $\|f+\operatorname{div} q\|_{H^{-1}(\Omega)}$ requires an approximation of the dual norm. The BPX precondition has been suggested to allow a practical variant and is an established LS. In general, one requires an approximation of the norm in $Y^{*}$ by the computable norm in $Y_{h}^{*}$ for a large but finite-dimensional space $Y_{h}$, the test-search space. This is not a Petrov-Galerkin scheme, so in fact, $\operatorname{dim} X_{h}<\operatorname{dim} Y_{h}$ in a minimum residual method. An effective computation, however, requires parallel computing and breaking the test norms in the sense that $Y_{h}$ is a finite-dimensional space of piecewise discontinuous functions. This allows for a piecewise computation in parallel. The mathematical framework is in product spaces.

## Continuous Problem 4 dPG

- $X(T), Y(T)$ real Hilbert spaces for any $T \in \mathcal{P}$ and

$$
X \subset \hat{X}:=\prod_{T \in \mathcal{P}} X(T) \quad \text { and } \quad Y:=\prod_{T \in \mathcal{P}} Y(T)
$$

- $b: \hat{X} \times Y \rightarrow \mathbb{R}$ is a bounded bilinear form with

$$
\begin{aligned}
& b\left(\left(x_{T}\right)_{T \in \mathcal{P},},\left(y_{T}\right)_{T \in \mathcal{P})}=\sum_{T \in \mathcal{P}} b_{T}\left(x_{T}, y_{T}\right)\right. \\
& 0<\beta=\inf _{\substack{x \in X \\
\|x\|_{X}=1}} \sup _{\substack{y \in Y \\
\|y\|_{Y}=1}} b(x, y)
\end{aligned}
$$

- Let $F \in Y^{*}$ and $u \in X$ satisfy $b(u, \bullet)=F$ in $Y$


## Discretization

Let $X_{h}(T) \subset X(T)$ and $Y_{h}(T) \subset Y(T)$ be finite-dimensional subspaces

$$
X_{h}:=X \cap \prod_{T \in \mathcal{P}} X_{h}(T) \quad \text { and } \quad Y_{h}:=\prod_{T \in \mathcal{P}} Y_{h}(T)
$$

"dPG is a minimal residual method
$\left(\operatorname{minRes}_{h}\right) \quad u_{h} \in \underset{x_{h} \in X_{h}}{\arg \min }\left\|b\left(x_{h}, \bullet\right)-F\right\|_{Y_{h}^{*}}$
with piecewise discontinuous test functions"
Alternative formulation. Seek $\left(u_{h}, v_{h}\right) \in X_{h} \times Y_{h}$ with
$\left(\mathrm{M}_{h}\right) \quad\left\{\begin{aligned} b\left(x_{h}, v_{h}\right) & =0 & & \text { for all } x_{h} \in X_{h} \\ \left(v_{h}, y_{h}\right)_{Y}+b\left(u_{h}, y_{h}\right) & =F\left(y_{h}\right) & & \text { for all } y_{h} \in Y_{h}\end{aligned}\right.$

## dPG as Mixed Problem

Brezzi splitting lemma. $\left(M_{h}\right)$ is well-posed iff

$$
0<\beta_{h}:=\inf _{\substack{x_{h} \in X_{h} \\\left\|x_{h}\right\|_{x=1}=1}}^{\left.\sup _{\substack{y_{h} \in Y_{h} \\\left\|y_{h}\right\|_{Y}=1}} b\left(x_{h}, y_{h}\right)\right)}
$$

Local annulation. For all $T \in \mathcal{P}$ let $P_{T}: Y(T) \rightarrow Y(T)$ be a bounded linear projection onto $Y_{h}(T)$ s.t. any $y_{T} \in Y(T)$ satisfies

$$
b_{T}\left(\bullet, y_{T}-P_{T} y_{T}\right)=0 \quad \text { in } X_{h}(T)
$$

Then

$$
0<\min _{T \in \mathcal{P}} \beta\left\|P_{T}\right\|^{-1} \leqslant \beta_{h}
$$

General theory of mixed formulations. For $u \in X$ with $b(u, \bullet)=F$,

$$
\left\|u-u_{h}\right\|_{X}^{2}+\left\|0-v_{h}\right\|_{Y}^{2} \leqslant\|b\| \gamma_{h}^{-1} \min _{x_{h} \in X_{h}}\left\|u-x_{h}\right\|_{X}^{2}
$$

## A Posteriori Error Analysis

Suppose $b(u, \bullet)=F$ is well-posed, then

$$
\left\|u-u_{h}\right\|_{X}^{2}+\left\|v_{h}\right\|_{Y}^{2} \approx\left\|b\left(\bullet, v_{h}\right)\right\|_{X^{*}}^{2}+\left\|F-b\left(u_{h}, \bullet\right)+\left(v_{h}, \bullet\right)_{Y}\right\|_{Y^{*}}^{2}
$$

Global annulation. $P:=\prod_{T \in \mathcal{P}} P_{T}$ fulfils $b(\bullet, y-P y)=0$ in $X_{h}$ for any $y \in Y, \beta_{h}>0$, and

$$
\left\|u-u_{h}\right\|_{X}^{2}+\left\|v_{h}\right\|_{Y}^{2} \approx \underbrace{\left\|v_{h}\right\|_{Y}^{2}}_{\text {computable }}+\underbrace{\|F \circ(1-P)\|_{Y *}^{2}}_{\text {higher order? }}
$$

$$
\text { for all }\left(x_{h}, y_{h}\right) \in X_{h} \times Y_{h} \text { replacing }\left(u_{h}, v_{h}\right)
$$

[C-Demkowicz-Gopalakrishnan, SINUM (2014)]

## Application to Poisson Model Problem

## Simplified dPG for Single Domain

Let $f \in L^{2}(\Omega)$ in open, bounded, polygonal Lipschitz domain $\Omega \subset \mathbb{R}^{2}$. Seek $u: \Omega \rightarrow \mathbb{R}$ with

$$
\text { (PMP) }-\Delta u=f \text { in } \Omega \quad \text { and } \quad u=0 \quad \text { on } \partial \Omega
$$

Test functions $w \in H^{1}(\Omega)$ require (unknown) boundary term $t=\partial u / \partial \nu$ on $\partial \Omega$ as new variable and lead to well-posed problem: Given $f \in L^{2}(\Omega)$, seek $(u, t) \in X:=H_{0}^{1}(\Omega) \times H^{-1 / 2}(\partial \Omega)$ with

$$
\int_{\Omega} \nabla u \cdot \nabla w \mathrm{~d} x-\left\langle t, \gamma_{0} w\right\rangle_{\partial \Omega}=\int_{\Omega} f w \mathrm{~d} x \quad \text { for all } w \in Y:=H^{1}(\Omega)
$$

## Traces

Theorem. $U \subset \mathbb{R}^{n}$ open, bounded Lipschitz domain

- $\exists \gamma_{0} \in L\left(H^{1}(U) ; L^{2}(\partial U)\right)$ with $\gamma_{0} w=\left.w\right|_{\partial U}$ for all $w \in H^{1}(U) \cap C^{0}(\bar{U})$
- $H^{1 / 2}(\partial U):=\gamma_{0}\left(H^{1}(U)\right)$ is a Hilbert space
- Let $H^{-1 / 2}(\partial U):=\left(H^{1 / 2}(\partial U)\right)^{*}$, then $\exists \gamma_{\nu} \in L\left(H(\operatorname{div}, U) ; H^{-1 / 2}(\partial U)\right)$ surjective with $\gamma_{\nu} q=\left.q\right|_{\partial U} \cdot \nu$ for all $q \in C^{1}\left(\bar{U} ; \mathbb{R}^{n}\right)$

Integration by Parts. Any $q \in H(\operatorname{div}, U)$ and $w \in H^{1}(U)$ satisfy

$$
\left\langle\gamma_{\nu} q, \gamma_{0} w\right\rangle_{\partial U}=\int_{U} q \cdot \nabla w \mathrm{~d} x+\int_{U} \operatorname{div} q \cdot w \mathrm{~d} x
$$

## Traces on the Skeleton

## Duality lemma.

$$
\|g\|_{H^{1 / 2}(\partial U)}:=\min _{\substack{h \in H^{1}(U) \\ \gamma_{0} h=g}}\|h\|_{H^{1}(U)}, \quad\|t\|_{H^{-1 / 2}(\partial U)}=\min _{\substack{q \in H(\operatorname{div}, U) \\ \gamma_{\nu} q=t}}\|q\|_{H(\operatorname{div}, U)}
$$

Let $\mathcal{T}$ be a regular triangulation of $\Omega$
Consequence. For $q=\left(q_{T}\right)_{T \in \mathcal{P}} \in H(\operatorname{div}, \mathcal{T}):=\prod_{T \in \mathcal{T}} H(\operatorname{div}, T)$,

$$
\gamma_{\nu}^{\mathcal{T}} q:=\prod_{T \in \mathcal{T}} \gamma_{\nu} q_{T}
$$

Define the Hilbert space $H^{-1 / 2}(\partial \mathcal{T}):=\gamma_{\nu}^{\mathcal{T}} H(\operatorname{div}, \Omega)$ with norm

$$
\|t\|_{H^{-1 / 2}(\partial \mathcal{T})}=\min _{\substack{q \in H(\operatorname{div}, \Omega) \\ \gamma_{\nu}^{\top} q=t}}\|q\|_{H(\operatorname{div}, \Omega)}
$$

## dPG for PMP and Triangulation $\mathcal{T}$

$$
\begin{aligned}
& X_{h}(T):=P_{1}(T) \times P_{0}(\mathcal{E}(T)) \subset X(T):=H^{1}(T) \times H^{-1 / 2}(\partial T) \\
& Y_{h}(T):=P_{1}(T) \subset Y(T):=H^{1}(T) \text { are Hilbert spaces for any } T \text { with }
\end{aligned}
$$ local bilinear form $b_{T}: X(T) \times Y(T) \rightarrow \mathbb{R}$,

$$
b_{T}\left(u_{T}, t_{T} ; w_{T}\right)=\int_{T} \nabla u_{T} \cdot \nabla w_{T} \mathrm{~d} x-\left\langle t_{T}, \gamma_{0} w_{T}\right\rangle_{\partial T}
$$

Improved version of the duality and splitting lemma [CDG16] lead for
$X:=H_{0}^{1}(\Omega) \times H^{-1 / 2}(\partial \mathcal{T}) \subset \prod_{T \in \mathcal{T}} X(T)$ and $Y:=\prod_{T \in \mathcal{T}} Y(T)$
to the inf-sup condition

$$
0<\sqrt{1-\frac{1}{\sqrt{1+\lambda_{1}}}} \leqslant \beta=\inf _{\substack{x \in X \\
\|x\|_{x=1}=1 \\
\sup _{\begin{subarray}{c}{y \in Y \\
\| y \\
Y} }}}\end{subarray}} b(x, y)
$$

## Low-order dPG for PMP

$$
X_{h} \equiv S_{0}^{1}(\mathcal{T}) \times P_{0}(\mathcal{E}) \quad \text { and } \quad Y_{h}=P_{1}(\mathcal{T})
$$

The nonconforming interpolation $P_{T}:=\mathcal{I}^{\text {nc }}$ has annulation property and

$$
\left\|F \circ\left(1-\mathcal{I}^{\mathrm{nc}}\right)\right\|_{Y^{*}} \leqslant \sqrt{1 / 48+j_{1,1}^{-1}}\left\|h_{\mathcal{T}} f\right\|_{L^{2}(\Omega)} .
$$

Experiment. $\Omega=(-1,1)^{2} \backslash[-1,0]^{2}, f(x, y)=0$ $u(r, \theta)=r^{2 / 3} \sin (2(\theta+\pi / 2) / 3) \quad$ (polar coordinates $(r, \theta)$ )

 - GUB (adaptiv)
$\rightarrow-\left|\left|u-u_{C}\right|\right| \mid$ (uniform)
$\rightarrow$ GUB (uniform)

## Low-order dPG for PMP



Figure : Triangulation plot with 496 elements ( 250 degrees of freedom for $u_{C}$ ) for adaptive mesh-refinement with GUB as refinement indicator and $\theta=0.3$

## Application to Stokes Equations

## Low-Order dPG for Stokes Equations

## The Stokes equations in pseudostress formulation.

Given $f \in L^{2}\left(\Omega ; \mathbb{R}^{n}\right)$ and $g \in H^{1}\left(\partial \Omega ; \mathbb{R}^{n}\right)$ for domain $\Omega \subseteq \mathbb{R}^{n}$, seek $u \in H^{1}\left(\Omega ; \mathbb{R}^{n}\right)$ and $\sigma \in H\left(\operatorname{div}, \Omega ; \mathbb{R}^{n \times n}\right) / \mathbb{R}$ with

$$
\begin{array}{rlrl}
\operatorname{dev} \sigma & =\mathrm{D} u & & \text { in } \Omega \\
-\operatorname{div} \boldsymbol{\sigma} & =f & & \text { in } \Omega \\
u & =g & & \text { along } \partial \Omega \\
\operatorname{dev} A:= & & \\
& & \\
\hline
\end{array}
$$

## Low-order dPG for Stokes Equations

$$
\begin{aligned}
& X_{h}(T):=P_{0}\left(T ; \mathbb{R}^{n \times n}\right) / \mathbb{R} \times P_{0}\left(T ; \mathbb{R}^{n}\right) \times P_{1}\left(\mathcal{E}(T) ; \mathbb{R}^{n}\right) \times P_{0}\left(\mathcal{E}(T) ; \mathbb{R}^{n}\right) \\
& X(T):=L^{2}\left(T ; \mathbb{R}^{n \times n}\right) \times L^{2}\left(T ; \mathbb{R}^{n}\right) \times H^{1 / 2}\left(\partial T ; \mathbb{R}^{n}\right) \times H^{-1 / 2}\left(\partial T ; \mathbb{R}^{n}\right) \\
& X: L^{2}\left(\Omega ; \mathbb{R}^{n \times n}\right) / \mathbb{R} \times L^{2}\left(\Omega ; \mathbb{R}^{n}\right) \times H_{0}^{1 / 2}\left(\partial \mathcal{T} ; \mathbb{R}^{n}\right) \times H^{-1 / 2}\left(\partial \mathcal{T} ; \mathbb{R}^{n}\right) \\
& \subset \prod_{T \in \mathcal{T}} X(T) \quad \text { while } \quad Y=\prod_{T \in \mathcal{T}} Y(T) \\
& Y_{h}(T):=R T_{0}\left(T ; \mathbb{R}^{n \times n}\right) \times P_{1}\left(T ; \mathbb{R}^{n}\right) \\
& Y(T):=H\left(\operatorname{div}, T ; \mathbb{R}^{n \times n}\right) \times H^{1}\left(T ; \mathbb{R}^{n}\right)
\end{aligned}
$$

For all $T \in \mathcal{T}$ let $b_{T}: X(T) \times Y(T) \rightarrow \mathbb{R}$ with

$$
\begin{aligned}
b_{T}(\boldsymbol{\sigma}, u, s, t ; \boldsymbol{\tau}, v)= & \int_{T} \boldsymbol{\sigma}: \mathrm{D}_{\mathrm{nc}} v \mathrm{~d} x+\int_{T} \operatorname{dev} \boldsymbol{\sigma}: \boldsymbol{\tau} \mathrm{d} x+\int_{T} u \cdot \operatorname{div}_{\mathrm{nc}} \boldsymbol{\tau} \mathrm{~d} x \\
& \quad-\left\langle t, \gamma_{0} v\right\rangle_{\partial T}-\left\langle\gamma_{\nu} \boldsymbol{\tau}, s\right\rangle_{\partial T} \\
F(\boldsymbol{\tau}, v):= & \int_{\Omega} f \cdot v \mathrm{~d} x+\left\langle\gamma_{\nu}^{\mathcal{T}} \boldsymbol{\tau}, \gamma_{0}^{\mathcal{T}} g\right\rangle_{\partial \mathcal{T}}
\end{aligned}
$$

## Low-Order dPG for Stokes Equations

- $\beta$ and $\beta_{h}$ are explicitly bounded in terms of the Friedrichs, tr-dev-div constant and the inf-sup constant of the mixed FEM $H\left(\operatorname{div}, \Omega: \mathbb{R}^{n \times n}\right) / \mathbb{R} \times L^{2}\left(\Omega: \mathbb{R}^{n}\right)$
- the data approximation error $\|F \circ(1-P)\|_{Y_{h}^{*}}$ is not necessarily of higher order
- the extension $\hat{Y}_{h}(T):=R T_{0}\left(T ; \mathbb{R}^{n \times n}\right) / \mathbb{R} \oplus b_{3}(T) \mathbb{R}_{\text {dev }}^{n \times n} \times P_{1}\left(T ; \mathbb{R}^{n}\right)$ of $Y_{h}(T)$ with the cubic bubble $b_{3}(T)$ guarantees the higher order
- the experiments compare the residual error estimators $\eta_{h}:=\left\|F-b\left(x_{h}, \bullet\right)\right\|_{Y_{h}^{*}}, \hat{\eta}_{h}:=\left\|F-b\left(x_{h}, \bullet\right)\right\|_{\hat{Y}_{h}^{*}}$, and the up to a generic constant guaranteed bound $\tilde{\eta}_{h}^{2}:=\hat{\eta}_{h}^{2}+\operatorname{osc}^{2}\left(g^{\prime}, \mathcal{E}(\partial \Omega)\right)$

Numerical Example: dPG for Stokes - colliding flow
Experiment. $\Omega=(-1,1)^{2}, f \equiv 0$ with implicit boundary data, for all $\left(x_{1}, x_{2}\right) \in \Omega, u\left(x_{1}, x_{2}\right)=4\left(5 x_{1} x_{2}^{4}-x_{1}^{5}, 5 x_{1}^{4} x_{2}-x_{2}^{5}\right)$ and $p\left(x_{1}, x_{2}\right)=120 x_{1}^{2} x_{2}^{2}-20\left(x_{1}^{4}+x_{2}^{4}\right)-16 / 3$.


| $\square$ | $\eta_{h}, \theta=1$ |
| :--- | :---: |
| - | $\hat{\eta}_{h}, \theta=1$ |
|  | $\tilde{\eta}_{h}, \theta=1$ |
| - | $x-x_{h} \\| x, \theta=1$ |

Numerical Example: dPG for Stokes - L-shaped domain Experiment. $\Omega=(-1,1)^{2} \backslash([0,1] \times[-1,0]), f \equiv 0$, for all $(r, \varphi) \in[0, \infty) \times[0,3 \pi / 2], \omega:=3 \pi / 2, \alpha:=856399 / 1572864$, $w(\varphi):=\frac{\sin ((1+\alpha) \varphi) \cos (\alpha \omega)}{1+\alpha}-\cos ((1+\alpha) \varphi)+\frac{\sin ((\alpha-1) \varphi) \cos (\alpha \omega)}{1-\alpha}+\cos ((\alpha-1) \varphi)$, with implicit boundary data, $p(r, \varphi)=\frac{-r^{\alpha-1}\left((1+\alpha)^{2} w^{\prime}(\varphi)+w^{\prime \prime \prime}(\varphi)\right)}{1-\alpha}$, and $u(r, \varphi)=\binom{r^{\alpha}\left((1+\alpha) \sin (\varphi) w(\varphi)+\cos (\varphi) w^{\prime}(\varphi)\right.}{-(1+\alpha) \cos (\varphi) w(\varphi)+\sin (\varphi) w^{\prime}(\varphi)}$


## Numerical Example: dPG for Stokes - L-shaped domain



Figure : Triangulation plot with 371 elements (3711 degrees of freedom) for adaptive mesh-refinement with $\eta_{\ell}$ and $\theta=0.3$

## Numerical Example: dPG for Stokes - backward facing step

 Experiment. $\Omega=((-2,8) \times(-1,1)) \backslash((-2,0) \times(-1,0)), f \equiv 0$, boundary data $g\left(x_{1}, x_{2}\right)= \begin{cases}1 / 10\left(-x_{2}\left(x_{2}-1\right), 0\right) & \text { for } x_{1}=-2, \\ 1 / 80\left(-\left(x_{2}-1\right)\left(x_{2}+1\right), 0\right) & \text { for } x_{1}=8, \\ (0,0) & \text { elsewhere. }\end{cases}$

$$
\begin{aligned}
& -\eta_{h}, \theta=1 \\
& -\tilde{\eta}_{h}, \theta=1 \\
& -\eta_{h}, \theta=0.9 \\
& -\eta_{h}, \theta=0.6 \\
& -\eta_{h}, \theta=0.3 \\
& \rightarrow \hat{\eta}_{h}, \theta=0.3 \\
& \rightarrow \eta_{h}, \theta=0.3
\end{aligned}
$$

## Numerical Example: dPG for Stokes - backward facing step



Figure: Triangulation plot with 1551 elements (15511 degrees of freedom) for adaptive mesh-refinement with $\eta_{\ell}$ and $\theta=0.3$

## Example for Linear Elasticity

## Low-Order dPG for Linear Elasticity

The Navier-Lamé equations. Seek $u \in H^{1}\left(\Omega ; \mathbb{R}^{n}\right)$ and $\sigma \in H(\operatorname{div}, \Omega ; \mathbb{S})$ with

$$
\begin{aligned}
-\operatorname{div} \sigma & =f & & \text { in } \Omega, \\
\sigma & =\mathbb{C} \varepsilon(u) & & \text { in } \Omega, \\
u & =0 & & \text { on } \Gamma_{D}, \\
\sigma \nu & =0 & & \text { on } \Gamma_{N},
\end{aligned}
$$

$\varepsilon(u):=\operatorname{sym} \mathrm{D} u:=\left(\mathrm{D} u+\mathrm{D} u^{\top}\right) / 2$, $\mathbb{C}(A):=2 \mu A+\lambda \operatorname{tr}(A) I_{n \times n}$.

## Low-Order dPG for Linear Elasticity

## Hilbert spaces.

$X(T):=L^{2}(T ; \mathbb{S}) \times L^{2}\left(T ; \mathbb{R}^{n}\right) \times H^{1 / 2}\left(\partial T ; \mathbb{R}^{n}\right) \times H^{-1 / 2}\left(\partial T ; \mathbb{R}^{n}\right)$
$Y(T):=H(\operatorname{div}, T ; \mathbb{S}) \times H^{1}\left(T ; \mathbb{R}^{n}\right)$
$X:=L^{2}(\Omega ; \mathbb{S}) / \mathbb{R} \times L^{2}\left(\Omega ; \mathbb{R}^{n}\right) \times H_{D}^{1 / 2}\left(\partial \mathcal{T} ; \mathbb{R}^{n}\right) \times H_{N}^{-1 / 2}\left(\partial \mathcal{T} ; \mathbb{R}^{n}\right)$
$X \subset \prod_{T \in \mathcal{T}} X(T), \quad Y:=\prod_{T \in \mathcal{T}} Y(T)$
Bilinear form. For all $T \in \mathcal{T}$ let $b_{T}: X(T) \times Y(T) \rightarrow \mathbb{R}$ with

$$
\begin{aligned}
b_{T}(\sigma, u, s, t ; \tau, v)= & \int_{T} \sigma: \varepsilon_{N C}(v) \mathrm{d} x+\int_{T} \mathbb{C}^{-1} \sigma: \tau \mathrm{d} x+\int_{T} u \cdot \operatorname{div}_{\mathrm{nc}} \tau \mathrm{~d} x \\
& -\left\langle t, \gamma_{0} v\right\rangle_{\partial T}-\left\langle\gamma_{\nu} \tau, s\right\rangle_{\partial T} .
\end{aligned}
$$

Discretization. $X_{h}(T):=P_{0}(T ; \mathbb{S}) / \mathbb{R} \times P_{0}\left(T ; \mathbb{R}^{n}\right) \times P_{1}\left(\mathcal{E}(T) ; \mathbb{R}^{n}\right) \times$
$P_{0}\left(\mathcal{E}(T) ; \mathbb{R}^{n}\right), Y_{h}(T):=\operatorname{sym} R T_{0}\left(T ; \mathbb{R}^{n \times n}\right) / \mathbb{R} \times P_{1}\left(T ; \mathbb{R}^{n}\right)$.

## Low-Order dPG for Linear Elasticity

- bounds of $\beta$ and $\beta_{h}$ depend on Friedrichs, Korn, tr-dev-div constant, the inf-sup constant of the mixed FEM and $\mu$, but are independent of $\lambda$
- canonical choice of norms (e.g., $\|\bullet\|$ on $L^{2}(\Omega ; \mathbb{S})$ ) lead to locking-free $L^{2}-H^{1}$ method
- energy method with other, $\mathbb{C}$-dependent norms (e.g., $\left\|\mathbb{C}^{1 / 2} \bullet\right\|$ on $\left.L^{2}(\Omega ; \mathbb{S})\right)$ suffers from locking
- extension like for Stokes equations yield a higher order data approximation error


## Example: Rotated L-shaped domain with exact solution



Numerical Example: Cook's membrane


## Numerical Example: Cook's membrane



## Numerical Example: Locking



## Application to Maxwell Equations

## Single Domain

$\Omega \subset \mathbb{R}^{3}$ open, bounded, polyhydral Lipschitz domain. Seek $E: \Omega \rightarrow \mathbb{R}^{3}$ with
(Maxwell) curlcurl $E-\omega^{2} E=J$ in $\Omega$ and $E \times \nu=0$ on $\partial \Omega$

Test functions $F \in H(\operatorname{curl}, \Omega)$ lead to boundary term $\hat{H}=\operatorname{curl} E \times \nu$ on $\partial \Omega$. Suppose $\omega^{2}$ is not a Maxwell eigenvalue. The resulting well-posed problem reads:

Given $J \in L^{2}\left(\Omega ; \mathbb{R}^{3}\right), \operatorname{seek}(E, \hat{H}) \in X:=H_{0}(\operatorname{curl}, \Omega) \times H^{-1 / 2}\left(\operatorname{div}_{\partial \Omega}, \partial \Omega\right)$

$$
\int_{\Omega} \operatorname{curl} E \cdot \operatorname{curl} F \mathrm{~d} x-\omega^{2} \int_{\Omega} E \cdot F \mathrm{~d} x-\left\langle\pi_{\tau} F, \hat{H}\right\rangle_{\partial \Omega}=\int_{\Omega} J \cdot F \mathrm{~d} x
$$

for all $H(\operatorname{curl}, \Omega)$

## Traces

Theorem. $U \subset \mathbb{R}^{3}$ open, bounded Lipschitz domain

- $\exists \gamma_{\tau} \in L\left(H(\right.$ curl,$\left.U) ; H^{-1 / 2}(\partial U)\right), \gamma_{\tau} H=\left.H\right|_{\partial U} \times \nu$ for $H \in C^{\infty}\left(\bar{U} ; \mathbb{R}^{3}\right)$
- $H^{-1 / 2}\left(\operatorname{div}_{\partial U}, \partial U\right):=\gamma_{\tau}(H(c u r l, U))$ is a Hilbert space
- Let $H^{-1 / 2}\left(\operatorname{curl}_{\partial U}, \partial U\right):=\left(H^{-1 / 2}\left(\operatorname{div}_{\partial U}, \partial U\right)\right)^{*}$, then $\exists \pi_{\tau} \in L\left(H(\right.$ curl,$U) ; H^{-1 / 2}\left(\right.$ curl $\left.\left._{\partial U}, \partial U\right)\right)$ surjective with $\pi_{\tau} F=\nu \times\left(\left.F\right|_{\partial U} \times \nu\right)$ for all $F \in C^{\infty}\left(\bar{U} ; \mathbb{R}^{3}\right)$

Integration by parts. Any $F, H \in H($ curl,$U)$ satisfy

$$
\left\langle\pi_{\tau} F, \gamma_{\tau} H\right\rangle_{\partial U}=\int_{U} H \cdot \operatorname{curl} F \mathrm{~d} x-\int_{U} \operatorname{curl} H \cdot F \mathrm{~d} x
$$

## Traces on the Skeleton

## Duality lemma.

$$
\begin{aligned}
\|\hat{H}\|_{H^{-1 / 2}\left(\operatorname{div}_{\partial U}, \partial U\right)} & :=\min _{\substack{H \in H(\operatorname{curl}, U) \\
\gamma_{T} H=\hat{H}}}\|H\|_{H(\text { curl }, U)} \\
\|\hat{F}\|_{H^{-1 / 2}\left(\operatorname{curl}_{\partial U}, \partial U\right)} & =\min _{\substack{F \in H\left(\operatorname{curl}^{2}, U\right) \\
\gamma_{\nu} F=\hat{F}}}\|q\|_{H(\text { curl }, U)}
\end{aligned}
$$

Let $\mathcal{T}$ be a shape-regular triangulation of $\Omega$ into tetrahedra

Consequence. For $H=\left(H_{T}\right)_{T \in \mathcal{T}} \in \prod_{T \in \mathcal{T}} H(\operatorname{curl}, T)$ let

$$
\gamma_{\tau}^{\mathcal{T}} H:=\prod_{T \in \mathcal{T}} \gamma_{\tau} H_{T}
$$

Define the Hilbert space $H^{-1 / 2}\left(\operatorname{div}_{\partial \mathcal{T}}, \partial \mathcal{T}\right):=\gamma_{\mathcal{T}}^{\mathcal{T}} H($ curl,$\Omega)$ with norm

$$
\|\hat{H}\|_{H^{-1 / 2}\left(\operatorname{div}_{\partial \mathcal{T}, ~}, \mathcal{T}\right)}=\min _{\substack{H \in H(\operatorname{curl}, \Omega) \\ \gamma_{\nu}^{\mathcal{T}} H=\hat{H}}}\|H\|_{H(\operatorname{curl}, \Omega)}
$$

## dPG for Maxwell and Triangulation $\mathcal{T}$

$$
\begin{aligned}
& X(T)=H(\text { curl, } T) \times H^{-1 / 2}\left(\operatorname{div}_{\partial T}, \partial T\right) \text { and } Y(T)=H(\text { curl, } T) \\
& X:=H_{0}(\text { curl }, \Omega) \times H^{-1 / 2}\left(\operatorname{div}_{\partial \mathcal{T}}, \partial \mathcal{T}\right) \subset \prod_{T \in \mathcal{T}} X(T) \text { and } \\
& Y:=\prod_{T \in \mathcal{T}} Y(T) \text { lead in }(\text { Maxwell }) \text { for all } T \in \mathcal{T} \text { to } \\
& b_{T}: X(T) \times Y(T) \rightarrow \mathbb{R} \text { with } \\
& b_{T}\left(E_{T}, \hat{H}_{T} ; F_{T}\right)=\int_{T} \operatorname{curl} E_{T} \cdot \operatorname{curl} F_{T} \mathrm{~d} x-\omega^{2} \int_{T} E_{T} \cdot F_{T} \mathrm{~d} x-\left\langle\pi_{\tau} F_{T}, \hat{H}_{T}\right\rangle_{\partial T}
\end{aligned}
$$

The duality and splitting lemma [CDG16] show for global bilinear form $b$

$$
0<\beta=\inf _{\substack{x \in X \\\|x\|_{X=1}=1}} \sup _{\substack{y \in Y \\\|y\|_{Y}=1}} b(x, y)
$$

## Discretization

Nédélec element. $N_{k}(T):=P_{k-1}\left(T ; \mathbb{R}^{3}\right) \oplus S_{k}\left(T ; \mathbb{R}^{3}\right)$ with
$S_{k}\left(T ; \mathbb{R}^{3}\right):=\left\{p \in P_{k}\left(T ; \mathbb{R}^{3}\right) \mid p\right.$ homogenous polynomial of degree $k$ and

$$
p(x) \cdot x=0 \text { in } T\}
$$

Discretization with Nédélec elements.

$$
X_{h}(T):=N_{k}(T) \times \gamma_{\tau} N_{k}(T) \quad \text { and } \quad Y_{h}(T):=N_{\ell}(T) \quad \text { for } k, \ell \in \mathbb{N}
$$

Annulation operator $P_{T}: Y(T) \rightarrow Y_{h}(T)$ in [CDG16] requires $\ell=k+3$
Numerical experiments with $k=1$ seems to work with $\ell=1$ as well

## Numerical Example. Primal dPG for Maxwell

$$
X_{h}(T):=N_{1}(T) \times \gamma_{\tau} N_{1}(T) \quad \text { and } \quad Y_{h}(T):=N_{\ell}(T)
$$

Experiment. $\quad \Omega=(0,1)^{3}, \quad \omega^{2}=1, \quad E=(\sin \pi x \sin \pi y \sin \pi z, 0,0)$ $k=1$, uniform refinement


$$
\begin{aligned}
& \bullet-\left\|E-E^{\mathrm{Ned}}\right\|_{H(\text { curl }, \Omega)}, \\
& \longrightarrow-\left\|E-E^{\mathrm{dPG}}\right\|_{H(\text { curl }, \Omega)}, \ell=1 \\
& \rightarrow\left\|\eta^{\mathrm{dPG}}\right\|_{Y}, \ell=1 \\
& \bullet-\left\|E-E^{\mathrm{dPG}}\right\|_{H(\text { curl }, \Omega)}, \ell=2 \\
& \rightarrow\left\|\eta^{\mathrm{dPG}}\right\|_{Y}, \ell=2 \\
& \cdots-\left\|E-E^{\mathrm{dPG}}\right\|_{H(\text { curl }, \Omega)}, \ell=3 \\
& \cdots-\left\|\eta^{\mathrm{dPG}}\right\|_{Y}, \ell=3
\end{aligned}
$$

## Numerical Example. Primal dPG for Maxwell

$$
X_{h}(T):=N_{1}(T) \times \gamma_{\tau} N_{1}(T) \quad \text { and } \quad Y_{h}(T):=N_{\ell}(T)
$$

Experiment. $\quad \Omega=(-1,1)^{3} \backslash[0,1]^{3}$ (Fichera's corner domain), $\omega^{2}=3.1$

$$
E=\left(e^{i \omega z}, e^{i \omega x}, e^{i \omega y}\right)
$$

Remark. $\omega^{2}$ is close to a Maxwell eigenvalue


$$
\begin{aligned}
& \bullet-\left\|E-E^{\mathrm{Ned}}\right\|_{H(\text { curl }, \Omega)} \\
& \longrightarrow-\left\|E-E^{\mathrm{dPG}}\right\|_{H(\text { curl }, \Omega)}, \ell=1 \\
& \bullet\left\|\eta^{\mathrm{dPG}}\right\|_{Y}, \ell=1 \\
& \bullet-\left\|E-E^{\mathrm{dPG}}\right\|_{H(\text { curl }, \Omega)}, \ell=2 \\
& \longrightarrow\left\|\eta^{\mathrm{dPG}}\right\|_{Y}, \ell=2 \\
& \cdots-\left\|E-E^{\mathrm{dPG}}\right\|_{H(\text { curl }, \Omega)}, \ell=3 \\
& \cdots-\left\|\eta^{\mathrm{dPG}}\right\|_{Y}, \ell=3
\end{aligned}
$$

## Numerical Example. Primal dPG for Maxwell

$$
X_{h}(T):=N_{1}(T) \times \gamma_{\tau} N_{1}(T) \quad \text { and } \quad Y_{h}(T):=N_{\ell}(T)
$$

Experiment. $\quad \Omega=(-1,1)^{3} \backslash[0,1]^{3}$ (Fichera's corner domain), $\omega^{2}=3.2$

$$
E=\left(e^{i \omega z}, e^{i \omega x}, e^{i \omega y}\right)
$$

Remark. $\omega^{2}$ is close to a Maxwell eigenvalue


$$
\begin{aligned}
& \longrightarrow\left\|E-E^{\mathrm{Ned}}\right\|_{H(\text { curl }, \Omega)} \\
& \longrightarrow\left\|E-E^{\mathrm{dPG}}\right\|_{H(\text { curl }, \Omega)}, \ell=1 \\
& \longrightarrow\left\|\eta^{\mathrm{dPG}}\right\|_{Y}, \ell=1 \\
& \longrightarrow\left\|E-E^{\mathrm{dPG}}\right\|_{H(\text { curl }, \Omega)}, \ell=2 \\
& \longrightarrow\left\|\eta^{\mathrm{dPG}}\right\|_{Y}, \ell=2 \\
& \cdots-\left\|E-E^{\mathrm{dPG}}\right\|_{H(\text { curl }, \Omega)}, \ell=3 \\
& \rightarrow-\left\|\eta^{\mathrm{dPG}}\right\|_{Y}, \ell=3
\end{aligned}
$$

## Numerical Example. Singular Solution

$$
X_{h}(T):=N_{1}(T) \times \gamma_{\tau} N_{1}(T) \quad \text { and } \quad Y_{h}(T):=N_{1}(T)
$$

Experiment. $\quad \Omega=(-1,1)^{3} \backslash[0,1]^{3}$ (Fichera's corner domain), $\omega^{2}=1$

$$
E=\nabla p(x, y, z) \text { with } p(x, y, z)=\left(x^{2}+y^{2}+z^{2}+10^{-6}\right)^{1 / 4}
$$

Remark. Singularity in $(x, y, z)=0$


$$
\begin{aligned}
& \bullet\left\|E-E^{\mathrm{Ned}}\right\|_{H(\mathrm{curl}, \Omega)}, \theta=1 \\
& \multimap\left\|E-E^{\mathrm{dPG}}\right\|_{H(\mathrm{curl}, \Omega)}, \theta=.3 \\
& \multimap\left\|\eta_{h}^{\mathrm{dPG}}\right\|_{Y}, \theta=.3
\end{aligned}
$$

## Numerical Example. [CDG16]

Experiment. $J=0$ and $\omega^{2}=25$ with boundary condition $\nu \times E=\nu \times E^{D}$, where $E^{D}(x, y, z)=(\sin \pi y, 0,0)$


Figure: Iteration 1, 5, and 9

## Numerical Example. [CDG16]

Remark. Since $\omega$ is large, the initial grid is too coarse for standard discretizations, but adaptive dPG seems to work


## Flexible Modelling

There exist equivalent [CDG16] formulations of (Maxwell), e.g. the first-order system

$$
i \omega E+\operatorname{curl} H=J \quad \text { and } \quad-i \omega H+\operatorname{curl} E=0
$$

It leads to the dPG method for the ultra-weak formulation

- X $(T)=L^{2}\left(T ; \mathbb{C}^{3}\right) \times L^{2}\left(T ; \mathbb{C}^{3}\right) \times \gamma_{\tau} H\left(\right.$ curl, $\left.T ; \mathbb{C}^{3}\right) \times \gamma_{\tau} H\left(\right.$ curl, $\left.T ; \mathbb{C}^{3}\right)$
- $X=L^{2}\left(\Omega ; \mathbb{C}^{3}\right) \times L^{2}\left(\Omega ; \mathbb{C}^{3}\right) \times \gamma_{\tau}^{\mathcal{T}} H_{0}\left(\right.$ curl,$\left.\Omega ; \mathbb{C}^{3}\right) \times \gamma_{\tau}^{\mathcal{T}} H\left(\right.$ curl,$\left.\Omega ; \mathbb{C}^{3}\right)$
- $Y(T)=H\left(\right.$ curl, $\left.T ; \mathbb{C}^{3}\right) \times H\left(\right.$ curl, $\left.T ; \mathbb{C}^{3}\right), \quad Y=\prod_{T \in \mathcal{T}} Y(T)$
- $b_{T}(E, H, \hat{E}, \hat{H} ; F, G)=i \omega \int_{T} E \cdot \bar{F} \mathrm{~d} x+\int_{T} H \cdot \overline{\operatorname{curl} F} \mathrm{~d} x-\langle F, \hat{H}\rangle_{\partial T}$

$$
-i \omega \int_{T} H \cdot \bar{G} \mathrm{~d} x+\int_{T} E \cdot \overline{\mathrm{curl} G} \mathrm{~d} x-\langle G, \hat{E}\rangle_{\partial T}
$$

## Numerical Example. Ultra-weak dPG for Maxwell

$$
\begin{aligned}
& X_{h}(T)=P_{0}\left(T ; \mathbb{C}^{3}\right) \times P_{0}\left(T ; \mathbb{C}^{3}\right) \times \gamma_{\tau} N_{1}(T ; \mathbb{C}) \times \gamma_{\tau} N_{1}(T ; \mathbb{C}) \text { and } \\
& Y_{h}(T)=N_{\ell}\left(T ; \mathbb{C}^{3}\right) \times N_{\ell}\left(T ; \mathbb{C}^{3}\right)
\end{aligned}
$$

Experiment. $\quad \Omega=(0,1)^{3}, \quad \omega^{2}=1, \quad E=(\sin \pi x \sin \pi y \sin \pi z, 0,0)$ $k=1$, uniform refinement



## Adaptive Least-Squares FEM

## Adaptive LSFEM 4 Stokes - Backward Facing Step

$\Omega=((-2,8) \times(-1,1)) \backslash((-2,0) \times(-1,0)), f \equiv 0$,
boundary data $g\left(x_{1}, x_{2}\right)= \begin{cases}1 / 10\left(-x_{2}\left(x_{2}-1\right), 0\right) & \text { for } x_{1}=-2, \\ 1 / 80\left(-\left(x_{2}-1\right)\left(x_{2}+1\right), 0\right) & \text { for } x_{1}=8, \\ (0,0) & \text { elsewhere }\end{cases}$

$$
L S(f ; \sigma, u):=\|f+\operatorname{div} \sigma\|_{L^{2}(\Omega)}\|\operatorname{dev} \sigma-\mathrm{D} u\|_{L^{2}(\Omega)}
$$



Figure : Triangulation plot with with 1473 triangles ( 5895 degrees of freedom ) for adaptive mesh-refinement with $\eta_{\ell}$ and $\theta=0.5$

Adaptive LSFEM - Adaptive Algorithm with Separate Marking


## Adaptive LSFEM - Quasi-Optimal Convergence

Non-linear approximation class $\mathcal{A}_{s}(u, f) \in \mathcal{A} \times L^{2}\left(\Omega ; \mathbb{R}^{2}\right)$ with

$$
|(u, f)|_{\mathcal{A}_{s}}^{2}:=\sup _{N \in \mathbb{N}} N^{2 s} E(u, f, N)<\infty
$$

## Best possible error

$$
\begin{aligned}
& E(u, f, N) \\
& \quad:=\min _{\substack{\mathcal{T} \in \mathbb{T} \\
|\mathcal{T}|-\left|\mathcal{T}_{0}\right| \leqslant N}}\left(\min _{\left(\tau_{\mathrm{LS}}, v_{\mathrm{LS}}\right) \in \Sigma(\mathcal{T}) \times \mathcal{A}(\mathcal{T})} \mathrm{LS}\left(f ; \tau_{\mathrm{LS}}, v_{\mathrm{LS}}\right)+\operatorname{osc}^{2}\left(g^{\prime}, \mathcal{E}(\partial \Omega)\right)\right)
\end{aligned}
$$

Optimal convergence rate $\exists 0<\kappa_{0}<\infty \exists 0<\theta_{0}<1 \forall 0<\kappa \leqslant \kappa_{0}$ $\forall 0<\theta \leqslant \theta_{0} \forall 0<\rho<1 \forall 0<s<\infty$,

$$
\sup _{\ell \in \mathbb{N}}\left(\left|\mathcal{T}_{\ell}\right|-\left|\mathcal{T}_{0}\right|\right)^{2 s}\left(\operatorname{LS}\left(f ; \sigma_{\ell}, u_{\ell}\right)+\operatorname{osc}^{2}\left(g^{\prime}, \mathcal{E}_{\ell}(\partial \Omega)\right)\right) \leqslant C_{\mathrm{opt}}|(u, f)|_{\mathcal{A}_{s}}^{2}
$$

$C_{\text {opt }}$ depends solely on $\mathcal{T}_{0}, s, \kappa, \theta, \rho$

## Adaptive LSFEM - Quasi-Optimal Convergence - Proof



## Adaptive LSFEM - Quasi-Optimal Convergence - Proof



## Adaptive LSFEM - Quasi-Optimal Convergence - Proof



## Adaptive LSFEM - Quasi-Optimal Convergence - Proof



## Conclusions

- Comprehensive abstract theory for dPG as a mixed method and/or as a minimum residual method
- More stable and smaller pre-asymptotic range than other/standard methods (e.g. Nédélec-FEM for Maxwell)
- Test search space can be small without loosing stability in the examples presented
- Work in progress on
- Guaranteed upper error bounds
- Adaptive mesh design
- Time-evolving dPG
- dPG for non-linear problems (e.g. eigenvalue computation)


## References I

© C．Carstensen，D．Gallistl，F．Hellwig，L．Weggler：Low－order dPG－FEM for an elliptic PDE，Computers \＆Mathematics with Applications 68 （11），1503－1512， 2014.
圊 C．Carstensen，L．Demkowicz，J．Gopalakrishnan：A posteriori error control for DPG methods，SIAM Journal on Numerical Analysis 52 （3）， 1335－1353， 2014.
（ C．Carstensen，L．Demkowicz，J．Gopalakrishnan：Breaking spaces and forms for the DPG method and applications including Maxwell equations，ICES， 2016 （submitted）．
目 C．Carstensen，F．Hellwig：Low－order dPG－FEMs for linear elasticity， SINUM， 2016 （submitted）．
专 C．Carstensen，S．Puttkammer：A low－order discontinuous Petrov－Galerkin Method for the Stokes Equations，（in preparation）．

## References II

A. Cohen, W. Dahmen, and G. Welper: Adaptivity and variational stabilization for convection-diffusion equations, ESAIM Math. Model. Numer. Anal. 46(5), 1247-1273, 2012.
P. Bringmann, C. Carstensen: An Adaptive Least-Squares FEM for the Stokes Equations with Optimal Convergence Rates, Numerische Mathematik, 2016 (submitted).
C. Carstensen, H. Rabus: Axioms of Adaptivity for Separate Marking, 2016 (in progress).

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